Automatic Detection of Epilepsy using Soft Computing Techniques

Synopsis

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Doctor of Philosophy

In

EEG Signal Processing

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Introduction

1.1. EEG Details

EEG signal is small electric potentials generated by neurons in human brain, measured by electrodes placed over the human scalp with the help of water-based gel to improve the conductance. [1] EEG is the commonly preferred non-invasive brain mapping technique [2]. Also, EEG is a form of the electric energy coming from various points on the human scalp representing a person's mental states and their variations. For example, EEG representation of a mental state (Contingent Negative Variation) voltage, representing a state of prediction. Other example is an EEG alpha wave which represents a person who is awake and relaxed with eyes closed [3]. From awake state to deep sleep, there is a change in EEG activity, slowing from beta wave (around 18 Hz) to theta-delta wave (3.5 to 8 Hz). Figure 1 below shows the major brain wave frequencies.

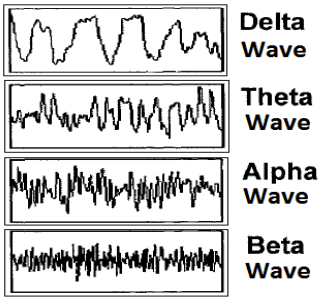


Figure 1. Waveform appearances of four brain rhythms [4].

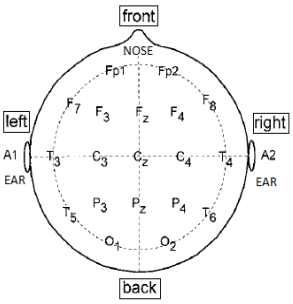


Figure 2, The 10-20 lead system for placing EEG electrodes [4].

Generally, EEG is used to study the different stages of sleep, and the effects of different medications on sleep stage. Mainly EEG is used in the analysis of epilepsy detection and diagnostic uses that find to decide epileptic seizure onset. The medical EEG is normally studied using silver–silver chloride electrodes placed over the human scalp in a standard setting known as the *10-20* International Lead System shown in Figure 2. It is called so as electrodes are placed at 10 or 20% of the distances from

anatomical markers on the human scalp. EEG electrodes are commonly used in differential pairs for good sensitivity to bio-electric potentials between a standard pair of electrodes. The alpha wave has highest energy in the occipital lobe of the brain, whereas the beta wave is maximum in the frontal lobe of the brain. [4]

1.2 Evoked EEG Potentials:

When an input stimulus is given to the brain through the sensory nervous system, for example a tone burst in the ear, a flash of light in the eye, or a mechanical or electric input stimulus to the skin or nerve, there is some response in the EEG called evoked response, and it shows the sensing and processing of events within the human brain. The magnitude of evoked potentials varies in the range of 3 to 20 μV. The response of human brain to these input stimuli is so small that they are difficult to detect in the presence of noise due to other bio-electric potentials of human brain. But, if the input stimuli are repetitive, then signal averaging can be used to derive the respective bioelectric potential. Examples of different evoked potentials are the AER (auditory evoked response), VER (visual evoked response), and SER (Somato-sensory evoked response).

1.3 Event-related potentials (ERPs):

This includes the ENG and EEG due to external stimuli as light, sound, electrical etc. ERPs depend on the characteristics of stimulus and presentation of the stimuli. SER potentials are good for testing of the nervous system to the cerebral cortex. The Somato-sensory evoked potentials are taken from the surface of the human brain. [5]

1.4 EEG for Epileptic Seizure, Stroke and Alzheimer

Epilepsy is affecting 2% people in the world associated with incidents of sudden motor movements due to hyper-synchronous discharges known as epileptic seizures. EEG is commonly used for detecting epileptic seizures. WHO has estimated that many epilepsy cases can be treated if earlier diagnosis is performed. [6] Presently there are various neurological analysis methods available for detection of epilepsy like electroencephalography from normal electroencephalography to iEEG. But many medical professionals lack the knowledge of difference of seizures from other neurological problems like psychological problems and convulsive scope attacks. [7] Patients of Epilepsy having motor movements with fits (seizures) are frequent after Alzheimer's and stroke. [8] The main reason of Epileptic seizure is

an abnormal activity of large groups of neurons in the human brain. The epilepsy leads to different changes in cognition and psychological behaviour. Patients with epilepsy always have mental stress along with anxiety. [9]

During treatment of Alzheimer's disease, a new method by the name "neuronal activity topography" is devised having with a computer connected by internet. Alzheimer's anomalies affect the EEG waveforms. Some useful information involved can be found in EEG signals of Alzheimer's patients [10]. Epilepsy may also lead to untimely death of patients. Wrong diagnosis of 25% is reported due to high occurrence and serious problems of seizure attacks. Long-term EEG plots are required to record the brain's electrical potentials because seizures can occur within few hours, weeks, or months, and so on. [11] The EEG plots are usually checked by neurophysiologists to find the seizures but they are prone to disturbances from noise, art**e**facts and other interferences. Hence visual inspection of the EEG plots proves to be very tedious and difficult even for an experienced doctor. There are reports of about 80% of epilepsy incidences in developing countries. Therefore, automatic detection of Epilepsy can be very useful. [12] Major artefacts in EEG are ocular artefacts and scalp muscle potentials along with ECG. Other sources of noise are very high electrode impedance, electrode displacements, amplifier drifts, etc. The noise poses a major trouble for neurologists and its magnitude can be larger than brain potential of interest. [13] When-ever an artery serving blood from heart to the brain explodes or a clot poses hurdle to the blood flow the stroke happens and reduces supply of oxygen and nutrients causing ischemic stroke which is the main reason of morbidity and long duration disability in the world, and can cause death. Stroke accounts for approximately 10% of deaths and around 5% of health-care costs.

1.5 Seizures Classification

In 1981 ILAE proposed types of seizures as shown in Figure 3. In 2010 ILAE proposed a flexible multidimensional framework. The focal (FE) and the non-focal EEG(NFE) types are shown in Figure no.-4.

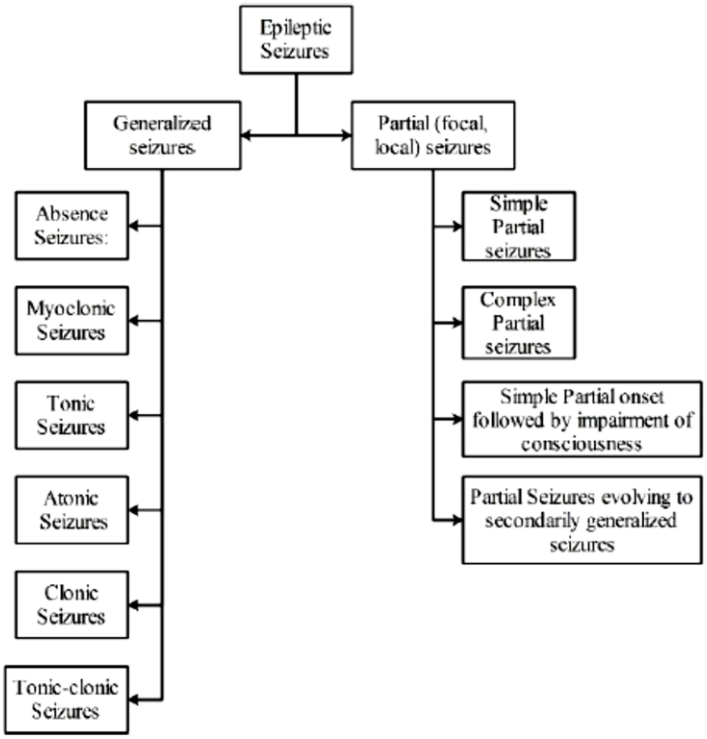


Figure 3: The Seizure Types [14]

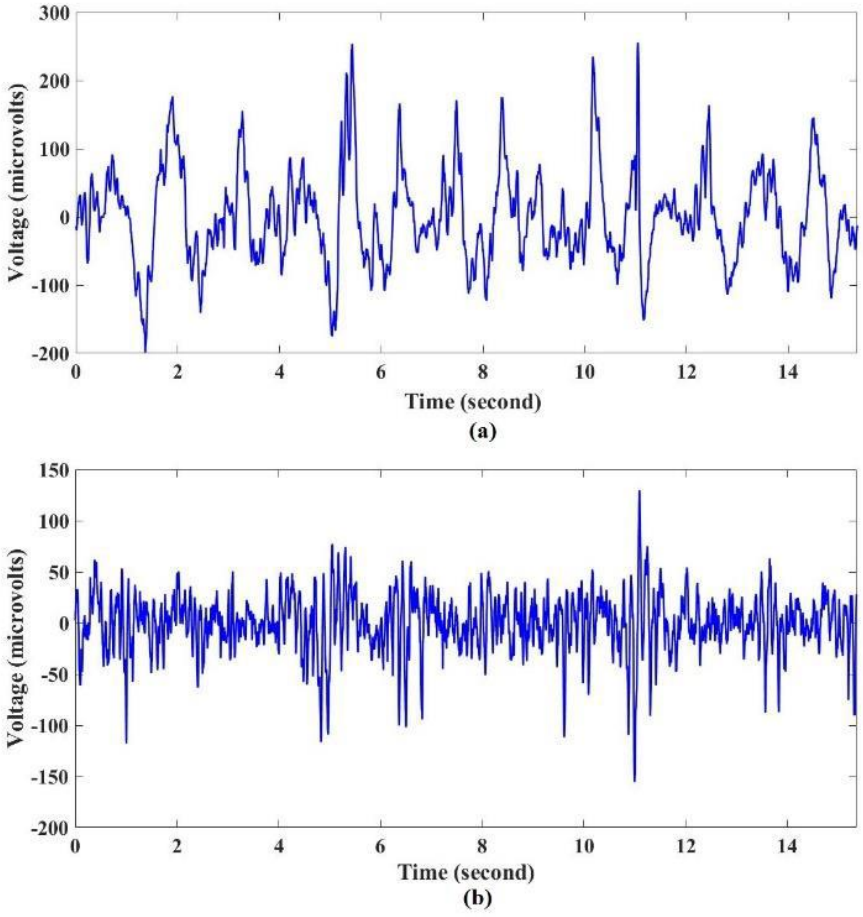


Figure 4: The EEG signal classification. [14]

A. *Detection of FE*

The seizure algorithm can detect the EEG signals of the existing seizures. Most seizure detection methods have two main steps:

1) Stage one includes features like the biomarkers.

2) Stage two uses a model-based feature for detecting seizures, known as the classification and uses a threshold mark taken from soft computing methods.

After including these features in a technique, there is a trade-off. Some methods use WT, PCA and spectral analysis. The different detection methods used are SVM, ANN, Fuzzy logic, HMM and CNN.

B. EEG pre-processing

The elimination of the EEG signal artifacts is complex but important task for the development of EEG analysis systems. Most important physiological artifacts are the Electro-Oculo-Graphy, respiration, and EMG due to body movements. There are many techniques for elimination the EEG artifacts using analog and digital filters.

C. *Discriminate Features in* T (time), F (frequency), T-F *and non-linear markers*

Normally the features are segregated as: T (time), F (frequency), T-F and non-linear. These features are taken from the EEG signals from many electrodes.

1) T domain features

EEG signals are non-stationary in nature but some EEG features in time domain can be useful as multiple stationary sections.

a) *Statistical feature analysis*

The EEG signal shows skewed distribution. The first order statistical parameters of EEG are the average and std. dev., but there are higher order features also which are very useful for these signals.

b) *Hjorth descriptors*

Hjorth described the different variables as the graphical parameters of EEG signals known as, "mobility", "activity" and "complexity of first order".

c) EEG Cross-Correlation (CCR)

It is similar to the convolution. Measuring the similarity among different signals is known as CCR. If correlation is performed with itself, then it is known as the ACR. Consider two signals as x(n) and y(n). The CCR between these signals is given by:

$$R_{xy}(m) = \sum_{n=0}^{N-m-1}(x(n+m)y(n)) \quad \text{for } m \geq 0 \text{----------(1)}$$

$$= R_{xy}(-m) \quad m<0$$

Where

m=⋯−2, −1,0,1, 2. is delay parameter.

d) PCA

PCA is used for converting the input domain into a lower dimensional domain, with a linear transformation. Eigenvectors is formed as:

$$x' = (x-\mu) \text{ ----------(2)}$$

e) ICA- The multivariate density function is defined as:

$$P(X(t)) = \prod_{i=1}^{c} P.Xi(t) \text{----------(3)}$$

Also:

$$Y(t) = A.X(t) \text{---------- (4)}$$

$$Z(t) = W.Y(t) = W.A.X(t) \text{---------- (5)}$$

f) LDA

It produces parameters to bind the predictors by increasing the differences across the sets of parameters. The discriminant scores are calculated as follows:

$$D=w_1.Z_1+ w_2.Z_2+ w_3.Z_3+\text{--------}+ w_n.Z_n \text{----------(6)}$$

The discriminant score equals the weighted linear predictor combination.

2) *F domain analysis*

It points to the details of the different frequency elements using FT (Fourier Transform). The PSD method is applied to study the FE and NFE types as shown below.

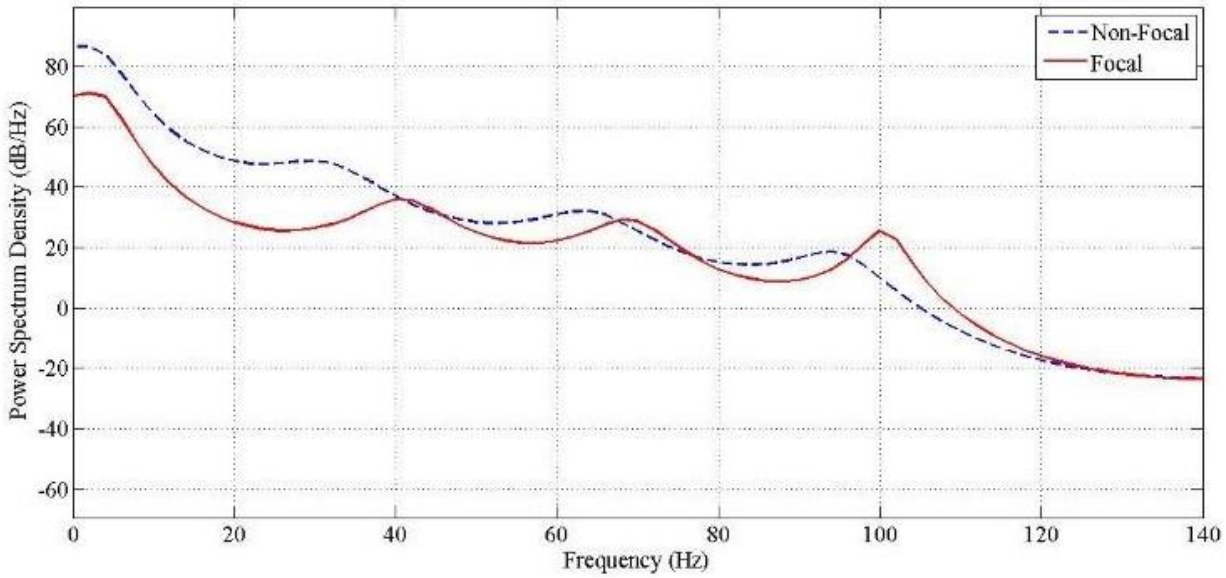


Figure 5. The PSD method. [14]

3) *T-F analysis*

It gives energy function in both the T and F domains for a signal.

a) *Discrete Wavelet Transform (DWT)*

DWT is diadatic in nature i.e. in the power of two. DWT uses HPF and LPF called Quadrature Mirror Filters as shown in Figure 6 below.

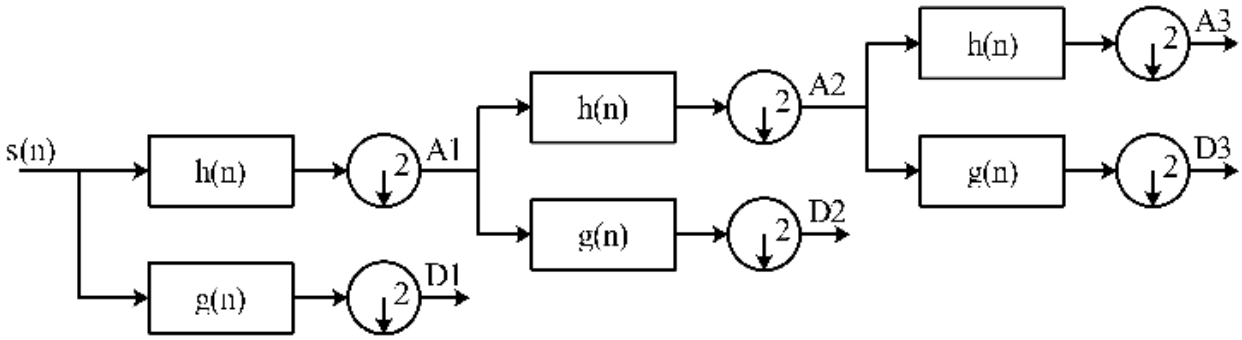


Figure 6. Wavelet division process. [14]

b) SPECTROGRAM

It shows a single analyzing technique which is applied for studying the multi-component non-stationary signals. Mathematically it is defined as follows:

$$P(t,\omega)=\left|\frac{1}{2\pi}\int e^{-j\omega\tau}\mathrm{s}(\tau)\mathrm{h}(\tau-\mathrm{t})\mathrm{d}\tau\right|^2 \text{ ----------(7)}$$

Spectrogram distribution is used for detecting the beginning of seizures.

c) Empirical Mode Decomposition (EMD)- It focuses to divide the signals into the Intrinsic Mode Functions (IMFs) as AM and FM waves as shown in Figure 7.

4) Non-Linear tools

The T and the F study cannot provide accurate results as they cannot find the smaller details from the EEG data due to their nonlinear behavior. Following are the Non-Linear tools used:

a) SAEM- (*Spectral Analysis Eigenvector Method)*

The Pisarenko algorithm calculates PSD. Following Polynomial has zeros on a unit circle:

$$K(f) = \sum_{k=0}^{m} a_k e^{-j2\pi fk} \text{ ----------(8)}$$

b) *Entropy*

It is estimated from PSD of the signal. But the embedding entropies are directly calculated using a time series.

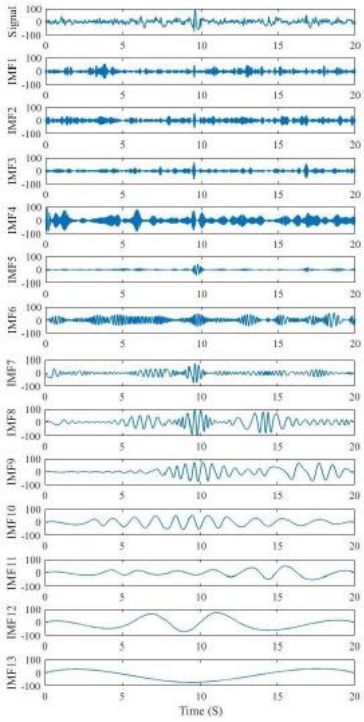


Figure 7. EEG IMFs Decompositions. [14]

5) Discriminate Features

Following tables present mathematical representations of discriminate EEG features. [15]

Table-1: EEG Time domain features.

Sl. No.	Feature Name	Mathematical Formula
1.	Mean	$F_1^{(t)} = \mu = \frac{1}{N}\sum_{n=1}^{N}\lvert z[n]\rvert$
2.	Variance	$F_2^{(t)} = \sigma^2 = \frac{1}{N}\sum_{n=1}^{N}\left(\mu - \lvert z[n]\rvert\right)^2$
3.	Skewness	$F_3^{(t)} = \frac{1}{N\sigma^3}\sum_{n=1}^{N}\left(\lvert z[n]\rvert - \mu\right)^3$
4.	Kurtosis	$F_4^{(t)} = \frac{1}{N\sigma^4}\sum_{n=1}^{N}\left(\lvert z[n]\rvert - \mu\right)^4$
5.	COF	$F_5^{(t)} = \frac{\sigma}{\mu} = \frac{\sqrt{F_2^{(t)}}}{F_1^{(t)}}$
6.	MAD	$F_6^{(t)} = \frac{1}{N}\sum_{n=1}^{N}\left(\lvert z[n]\rvert - \mu\right)$
7.	RMS	$F_5^{(t)} = \frac{\sigma}{\mu} = \sqrt{\frac{\sum_{n=1}^{N} z[n]^2}{N}}$
8.	IQR	$F_8^{(t)} = Z\left[\frac{3(N+1)}{4}\right] - Z\left[\frac{(N+1)}{4}\right]$
9.	Shannon entropy	$F_9^{(t)} = -\sum_{n=1}^{N} z[n]\log_2\left(z[n]\right)$

Note: z[n] is discrete EEG signal.

Table-2: EEG Frequency domain features.

Sl. No.	Feature Name	Mathematical Formula
1.	$P_{max}(f)$	$F_1^{(f)} = \sum_{k=1}^{\delta}\lvert Z[k]\rvert^2$ $F_2^{(f)} = \sum_{k=\delta+1}^{M}\lvert Z[k]\rvert^2$ $M \rightarrow f_{MAX}$
2.	Spectral centroid	$F_3^{(f)} = \sum_{k=1}^{M} k\lvert Z[k]\rvert \Big/ \sum_{k=1}^{M}\lvert Z[k]\rvert$
3.	Spectral flux	$F_3^{(f)} = \sum_{k=1}^{M} k\lvert Z[k]\rvert \Big/ \sum_{k=1}^{M}\lvert Z[k]\rvert$
4.	Spectral flatness	$F_4^{(f)} = \sum_{k=1}^{M}\left(Z^{(l)}[k] - Z^{(l-1)}[k]\right)^2$
5.	Spectral Roll-Off λ	$F_5^{(f)} = \left(\prod_{k=1}^{M} Z[k]\right)^{\frac{1}{M}}\left(\sum_{k=1}^{M} Z[k]\right)^{-1}$
6.	Spectral entropy	$F_6^{(f)} = \lambda\sum_{k=1}^{M}\lvert Z[k]\rvert$
7.	Spectral entropy	$F_7^{(f)} = \frac{1}{\log(M)}\sum_{k=1}^{M} P\left(Z[k]\right)\log P\left(Z[k]\right)$

Table-3: EEG time-frequency domain features

Sl. No.	Feature Name	Mathematical Formula
1.	Sub-bands energies	$F_1^{(tf)} = \sum_{n=1}^{N}\sum_{k=1}^{M_\delta}\rho[n,k]$ where $M_\delta = [M/f_s]$ & $M = (f_s/2)$ $F_2^{(tf)} = \sum_{n=1}^{N}\sum_{k=M_\delta+1}^{M}\rho[n,k]$
2.	Energy localization	$F_3^{(tf)} = \left(\prod_{n=1}^{N}\prod_{k=1}^{M}\rho[n,k]\right)^{\frac{1}{NM}} \Big/ \sum_{k=1}^{M}\sum_{n=1}^{N}\rho[n,k]$
3.	Mean and deviations	$F_4^{(tf)} = \frac{1}{N}\sum_{n=1}^{N} f_i[n]$ $F_5^{(tf)} = \max f_i[n] - \min f_i[n]$ where $f_i[n] = \frac{f_s}{2M}\left(\sum_{k=1}^{M} k\rho[n,k] \Big/ \sum_{k=1}^{M}\rho[n,k]\right)$
4.	Renyi entropy	$F_6^{(tf)} = \frac{1}{(1-\alpha)}\log_2\left(\sum_{n=1}^{N}\sum_{k=1}^{M}\rho^{\alpha}[n,k]\right)$

Table-4: QuadraticTFD Distributions

Sl. No.	Feature Name (QuadraticTFD)	TIME-LAG KERNEL (k [n, m])
1.	WVD	$\delta[n]$
2.	SMVD	$\delta[n]\omega[n]$
3.	CWD	$\frac{\sqrt{\pi\sigma}}{2\lvert m\rvert}\exp\left(\frac{-\pi^2\sigma n^2}{4m^2}\right)$**[sincn sincm]
4.	BD	$\left(\frac{\lvert 2m\rvert}{\cosh^2 n}\right)^{\beta}$*[sincm]
5.	MBD	$\frac{\cosh^{-2\beta} n}{\sum_n \cosh^{-2\beta} n}$
6.	Spectrogram	$\omega[n+m]\omega[n-m]$
7.	BJD	$\left[\frac{1}{4\lvert\alpha m\rvert} rect\left(\frac{n}{4\alpha m}\right)\right]$**[sincn sincm]
8.	ZAMD	$\left[\omega[m] rect\left(\frac{\alpha n}{4m}\right)\right]$**[sincn sincm]

6) C*lassification Algorithms*

After feature extraction, we can differentiate between the seizure and non-seizure EEG signals by a classification tool for the decision-making as shown in the table-5 below.

Table-5: Comparison of classification methods

Sl. No.	Feature Name	Classification Method	Accuracy
1	Entropy	Logistic regression	94.5%
2	FT	Decision tree	98.72%
3	T/F features	ANFIS	92.22%
4	WT	ME network	95%
5	T-F features	SVM	97.5%
6	Haralick descriptor- features	SVM	99%
7	Image texture features	SVM	98%
8	LBP	SVM	99.33%

Literature Survey

2.1 Seizure Detection and Performance Comparison of different methods

The block diagram of automatic seizure detection is depicted in Figure 8. [16]

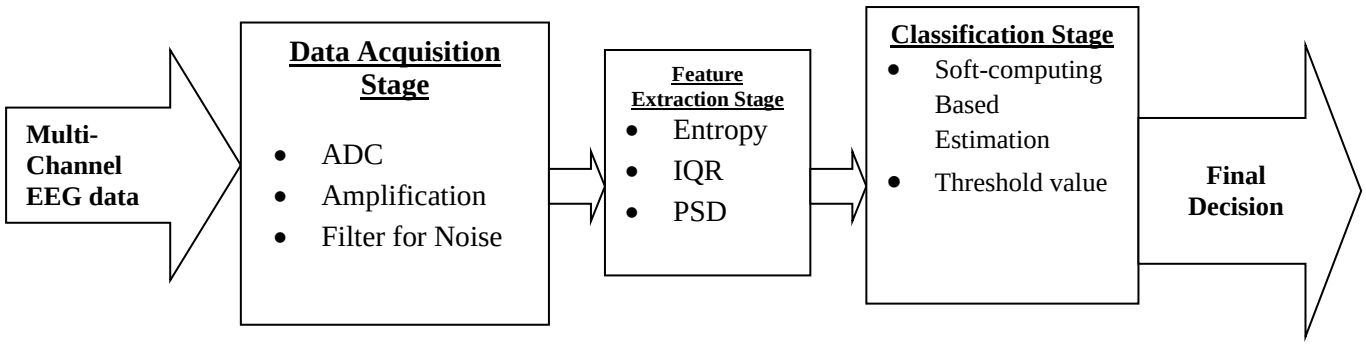


Figure 8: Automated Seizure Detection flow diagram.

Performance Parameters:

Following measures are used:

Sensitivity (SN): The measure to accurately classify the seizure as follows:

$$SN = \frac{TP}{(TP + FN)} \times 100\% \quad \ldots (9)$$

Specificity (SP): The measure to correctly classify the normal activities defined as follows:

$$SP = \frac{TN}{(TN + FP)} \times 100\% \quad \ldots (10)$$

Classification accuracy (CA): It is defined as follows as follows:

$$CA = \frac{TP + TP}{(TN + TP + FN + FP)} \times 100\% \quad \ldots (11)$$

Computation Complexity: The time required for classification in seconds.

COMPARATIVE ANALYSIS

The effectiveness of ANN and SVM classifiers are compared in Table-6 with respect to different feature extraction techniques. Table 7 shows results of the seizure detection of different classifiers and ANN shows good results comparable with SVM classifier. In cases where cost is a important factor SVM is a better option as it is only 1 % less accurate than ANN. Table 8 and 9 demonstrate the performance of the fuzzy classification approach.

Table-6: Comparison of ANN and SVM classifiers.

Parameters→ Combination of Techniques↓	**Classification Accuracy (%)**
Time Frequency with ANN	97.73
DWT with approximate entropy	96.65
WT with k-NN and ANN	100
DWT line length with MLP-ANN	97.77
DWT Inter-quartile range with SVM	99.66

Table-7: Comparison of different classifiers with Wavelet decomposition.

Parameters→ Techniques↓	**Classification Accuracy (%)**	**Specificity (%)**	**Sensitivity (%)**	**% Average Performance**
NBC	84.27	83.9	84.5	84.22
LDA	92.61	92.3	93	92.64
QDA	94.65	94.26	95	94.64
CART	92.36	92.04	93.21	92.54
ANN	97.7	97.25	98.28	97.74
k-NN	95.72	95	96.3	95.67
SVM	96.42	96	96.89	96.44

Table-8: Fuzzy Classification Results.

No. of Events	**No. of Correct**	**No. of Negatives**	**No. of False Positive**
216	200(92.6%)	16(7.4%)	35(16.2%)

Table-9 Overall recognition results

No. of Events	**No. of Correct**	**No. of False Negatives**	**No. of False Positive**
24	24(100%)	0(0%)	2(8.3%)

Table 10 shows the detection results of various classifiers with feature extraction from DWT of EEG signals. Table 11 shows the results of GA based classifier for the detection of epilepsy. [17]

Table-10: Detection results of various classifiers

Detection System	**Truly Trained (%)**	**Truly Tested (%)**	**Network Training Duration(sec)**

SVM Classifier	83.5	83.1	510
SVM Classifier with RBF	100	77.3	70
ANFIS Classifier	99.7	66.6	600
FBNN Classifier	96.0	79.6	90
ANFN Classifier	86.5	85.9	2700

Table-11: Results of Detection test using GA.

Parameter	**Number of Frames**	**Correct Classification (%)**
True Positive	29	36.25
True Negative	39	48.75
False Positive	1	1.25
False Negative	11	13.75
Total True	68	85

Seizure Detection with qualitative performance measures are compared in Table-12. [18]

Table-12- Qualitative performance measures

Sl. No.	**Algorithm**	**Methodology**	**Dataset**	**Application**	**Advantages**	**Limitation**
1	DSTFT	Basis function is complex.	Bonn.	Seizure Detection	Simple, Fast and better Frequency details.	Poor time details.
2	FT	FT applied to consecutive time window	EEG database of 24 years single patient.	BCI application	Fast Speed and better localization.	Fixed size Window
3	DWT with linear classifier	Includes MRA, CWT and DWT	Bonn.	Seizure Detection	Flexible size of window, Good T & F resolution	Choice of mother wavelet function (MWF).
4	GWT	Modified GWT	Gabor-based features	Emotion Recognition	Good T & F resolution	NA
5	Hjorth parameter	Based on choice of PFB and fisher ratio	BCI Competition data set.	BCI applications	Provision for Activity and mobility.	High Accuracy
6	HHT	Combination of EMD and HSA	Bonn Germany. Accuracy 98.5%	Seizure Detection	Overall good performance.	For narrow band EEG signals.
7	SMVD	Based on McAulay-Quatieri model	EEG database: Clinica Universitaria de Navarra.	Seizure Detection	Good T & F resolution,	Affected by cross parameter interference

2.2 HARDWARE IMPLEMENTATION -1:

Optimized Epilepsy Detection by Innovate FPGA:

The objective of this chip is to use Machine Learning algorithms to detect a seizure for a patient and trigger the electric stimuli that will be able to recover the brain back to its normal status, as shown in figure below.

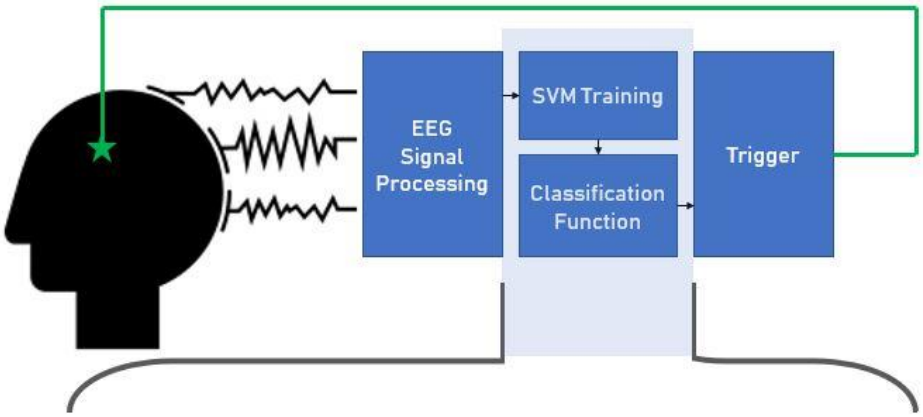


Figure 9. EEG Signal Classification. [19]

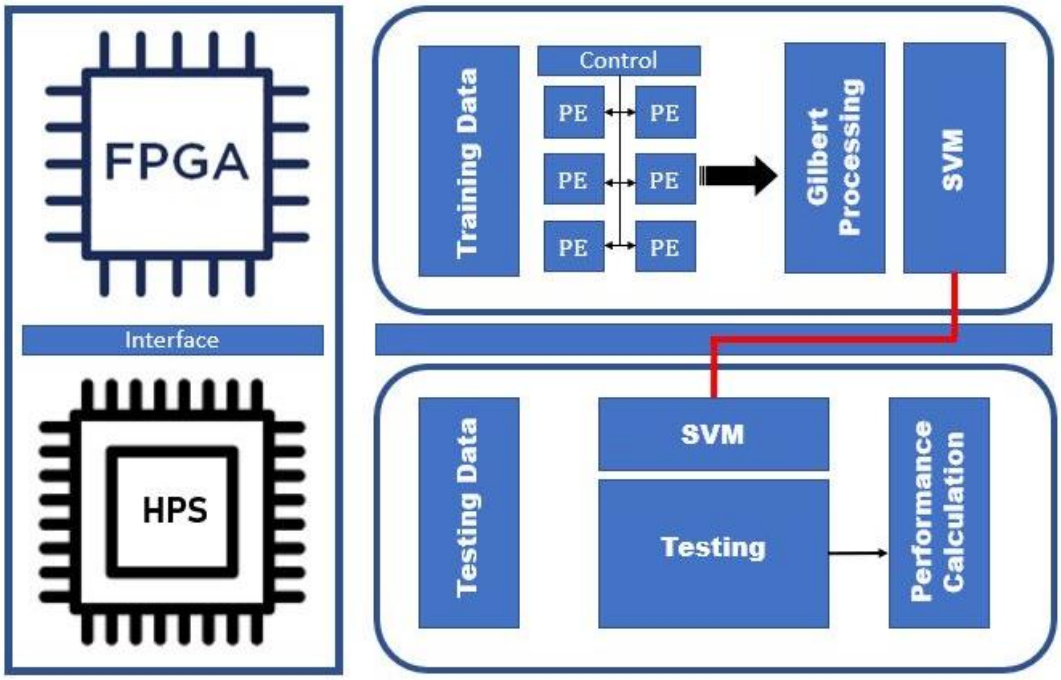


Figure 10: Block Diagram of Classification system in hardware. [19]

An FPGA device is used to test proof of concept. [19]

2.3 HARDWARE IMPLEMENTATION METHOD-2

1. EEG data-set

The EEG data set of University of BONN as shown in Figure 11 below. The measurement of the EEG data was done with 128-channels and at 173.6 Hertz sampling frequency with a 12-bit analog to digital converter, while digitization.

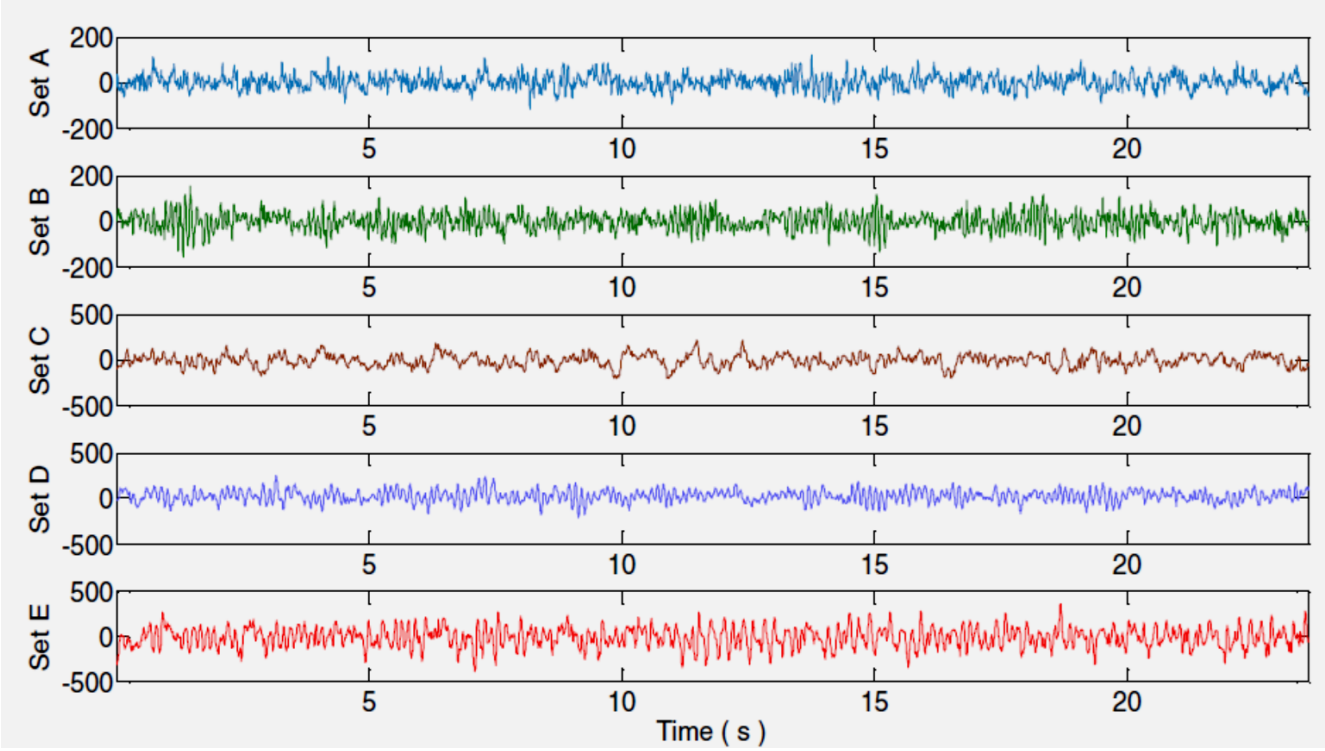
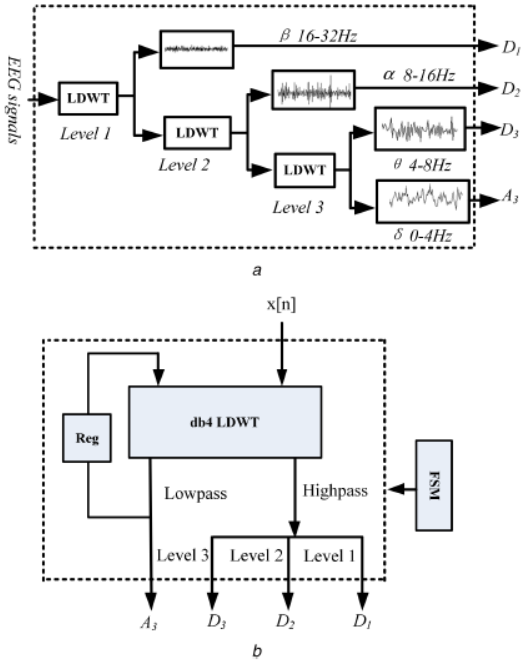


Figure11-Online EEG database of University of Bonn [12].

2. Feature Extraction Stage

The LDWT filters shown in Figure 13*a* requires lesser multipliers and architecture of the SD is drawn in Figure 14.



a) Figure12: Lifting-based Wavelet Architecture: (a) Traditional and (b) Improved. [20]

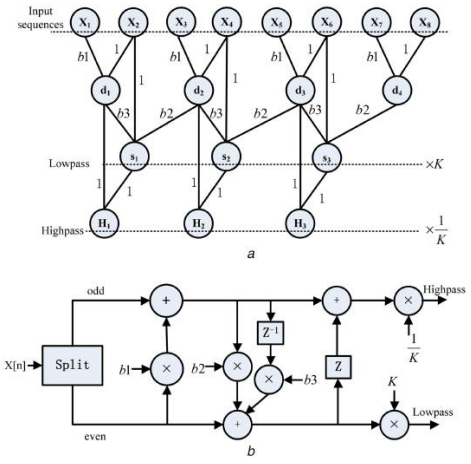


Figure13 db4 LDWT: (a) Method (b) Circuit [20]

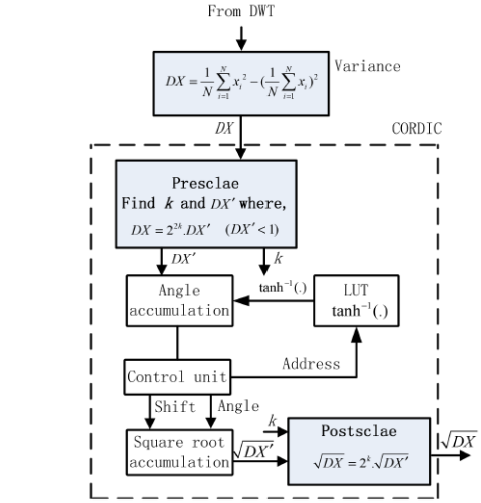


Fig. 4 *Architecture of the standard deviation*

Figure14 Standard Deviation Calculator [20]

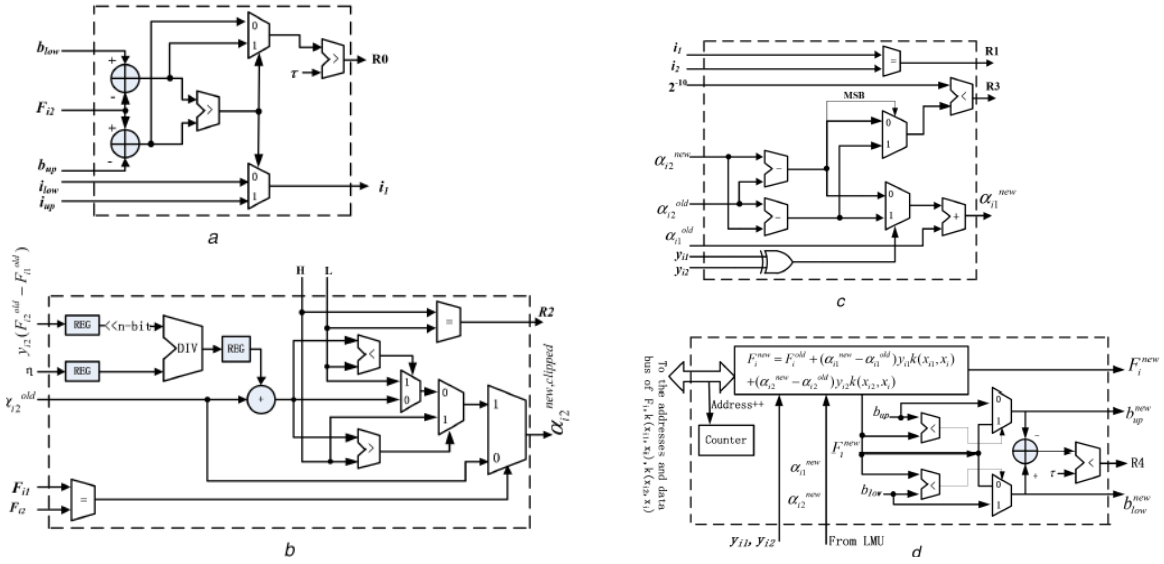


Figure15. Sub-module Circuits of MSMO Learning. [20]

3 Classification implementations

b) *Implementation of the MSMO:* There are four sub-modules in main circuit of MSMO learning in Figure15: Exam sub-module, a Lagrange sub-module, FBU sub-module, and an SMO control sub-module as shown in Table 13 below. [20]

Table-13: MSMO algorithm

Code Line No.	Pseudo-Code
1	Initial step: $\alpha_{i1} = 0$, $F_i = -y_i$, determining b_{up}, b_{low}, i_{up}, and i_{low}
2	Loop begin
3	Select index i_1 and i_2 corresponding α_{i1} and α_{i2}.
4	Update Lagrange multipliers α_{i2} and α_{i1}
5	Update F_i, b_{up}, and b_{low}

6	End loop (if all α_i's satisfy the KKT condition)
7	Final step: save Lagrange multipliers into classifier model

Implementation: Figure 16 below shows the architecture of 3 class SVM.

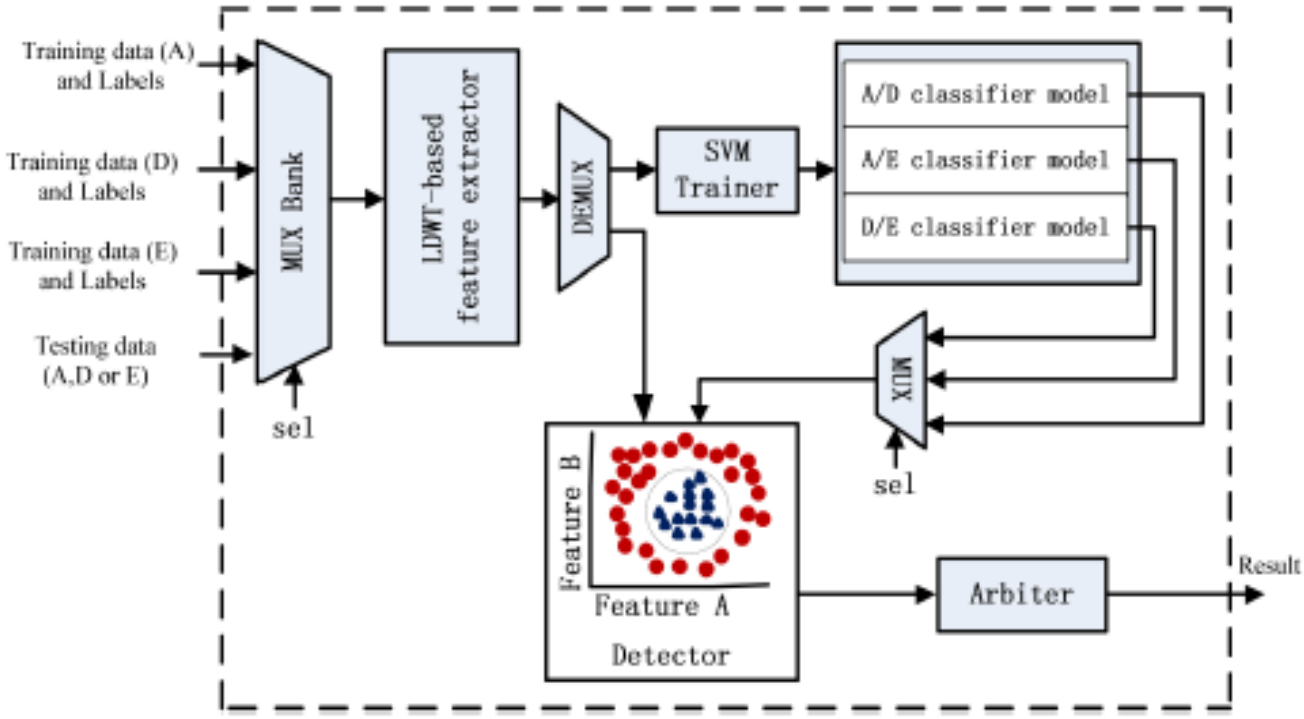


Figure16 SVM Three-Class Classification Architecture. [20]

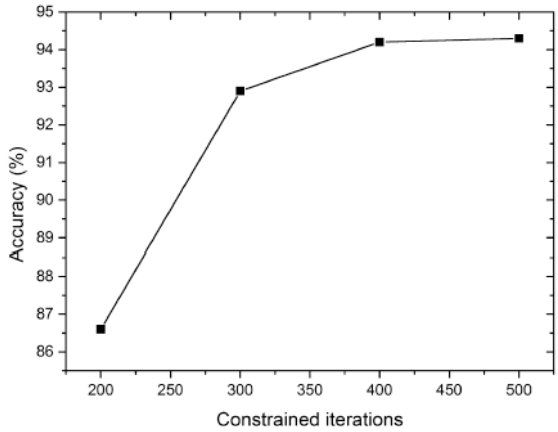


Figure17-Accuracy Vs Iterations. [20]

The circuit performance is shown in Table 14 below. The FPGA implementation specifications are given in Table 15. Table 16 shows the comparison of this work with previous works.

Table-14: Detection performance using A, D, and E

SETS↓	Sensitivity, %	Specificity, %	Accuracy, %
SET-A	96.0	97.0	94.2

SET-B	89.8	97.1	-
SET-C	97	97.3	-

Table-15: Resources utilized in the FPGA device.

Resource	Number Used	Total No. Available	Utilization, %
slice registers	28406	69120	41
Slice LUTs	49105	69120	71
LUT-FF	14906	43841	34
Bonded IOBs	167	640	26
BRAMs	86	148	58

2.4 State of the Art: CNN based Seizure Detector and Predictor Implementation

A) Source datasets: Datasets and Pre-processing

Here two datasets are used:

(i) MSSM dataset, and

(ii) CHB-MIT EEG dataset.

B) Wavelet Tensors: The WT is shown in Figure18.

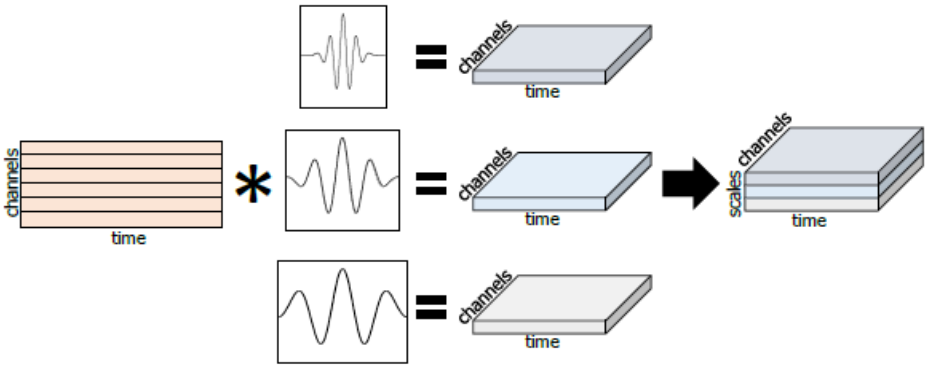


Figure18 Wavelet tensors. [21]

C. Methodology: Firstly, features are extracted from the EEG signal to differentiate among three functional states using CNN as shown in figure-19. As the preictal time length is not known already, the second task is to find preictal time length and prediction time using cross-validation. [21]

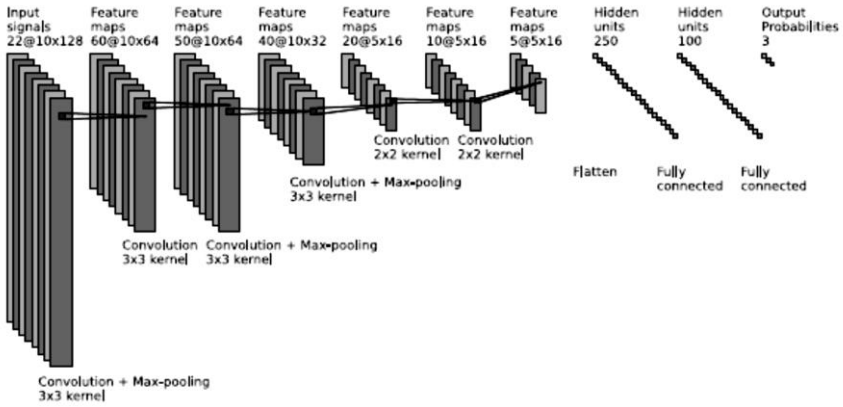


Figure19 Convolutional Neural Network. [21]

Here the pre-ictal period time is an important parameter and it is optimized over time. For validation of the preictal time, the different features from different pre-ictal time are analyzed.

D. *Methodology:*

The input to the CNN is given by calculating the WT on every EEG signal to get the tensors shown in Fig 19. After that we apply didactics 1 to 512 and the Mexican-hat MWF.

2.5 Options for Epilepsy predictor and detector systems:

2.5.1 CNN Based System-1

As it is shown in figure-20.

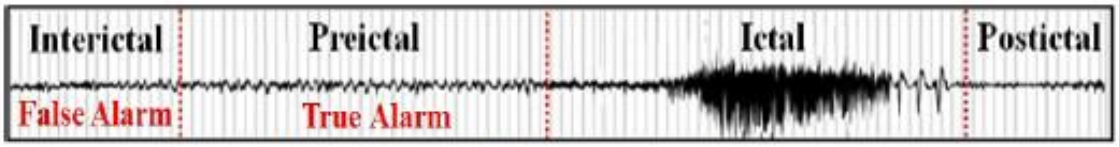


Figure 20. Brain states in a typical epileptic EEG recording. [22]

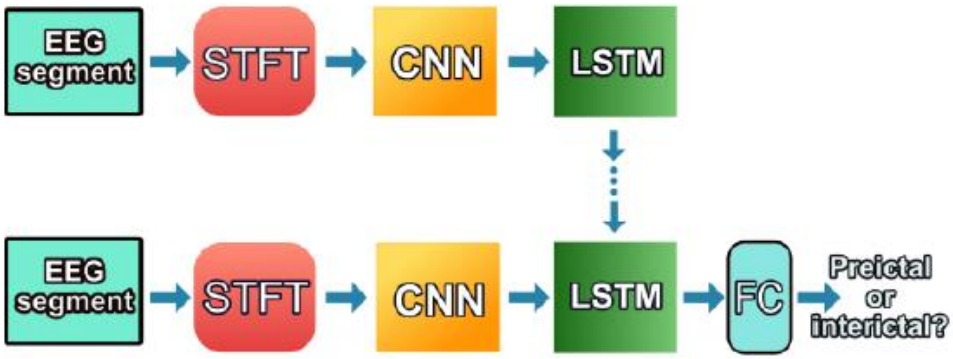


Figure 21. The diagram of the proposed model. [22]

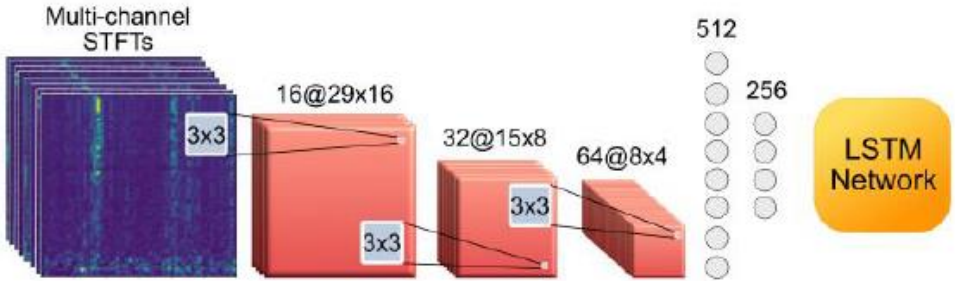


Figure 22. The proposed CNN architecture. [22]

A CNN-LSTM neural network as shown in figure-21 and 22 are trained on the STFTs extracted from EEG segments.

2.5.2 CNN Based System-2 As shown in Figure23 to 26. [23]

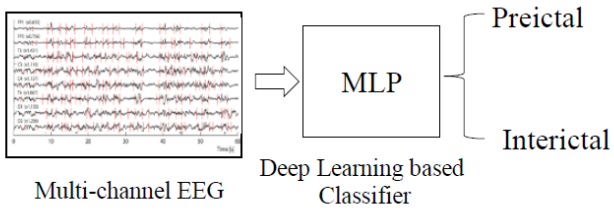


Figure 23. Block Diagram of MLP based predictor. [23]

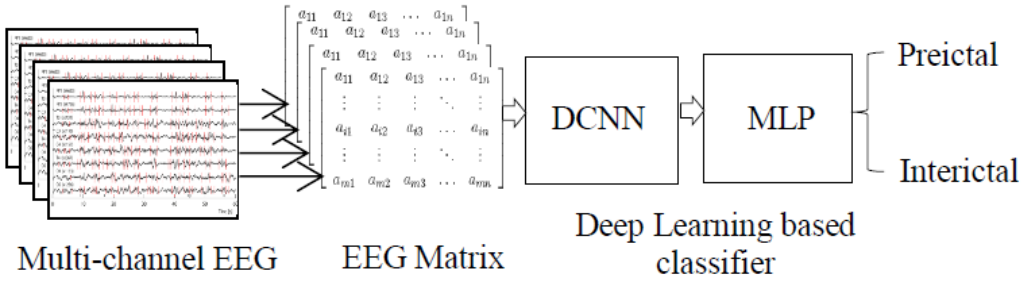


Figure 24. Block Diagram of DCNN + MLP. [23]

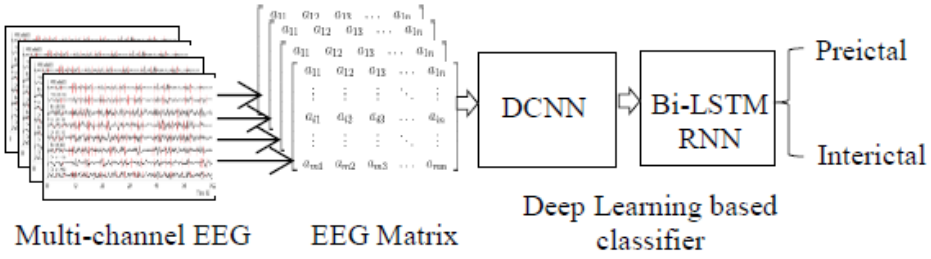


Figure 25. Block Diagram of DCNN + Bi-LSTM. [23]

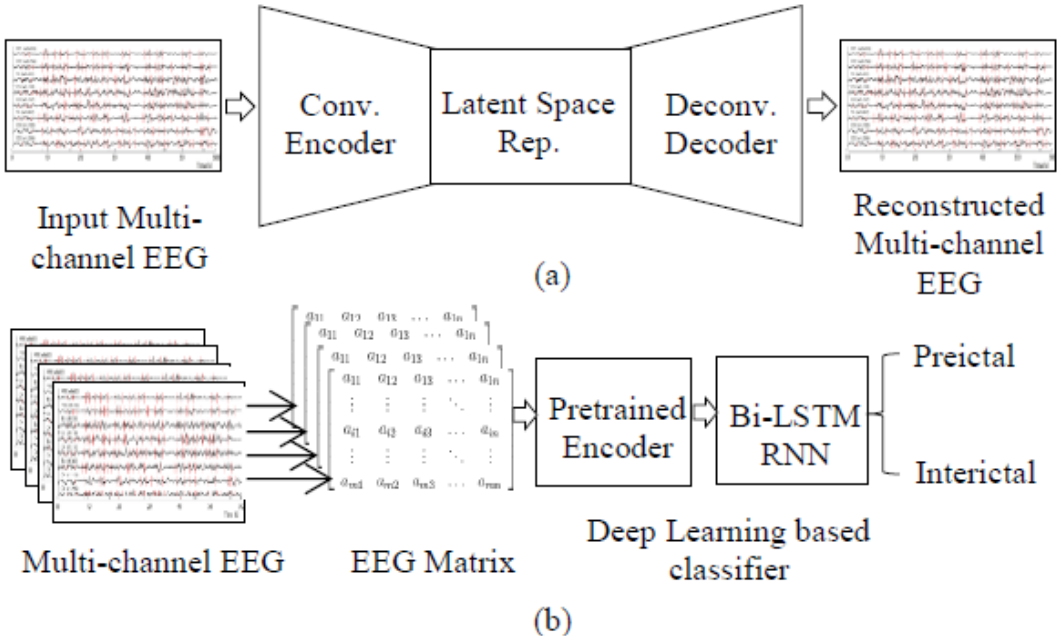


Figure26. Block Diagram of DCAE + Bi-LSTM model. [23]

2.5.3 CNN Based System-3

As shown in Figure 27. [24]

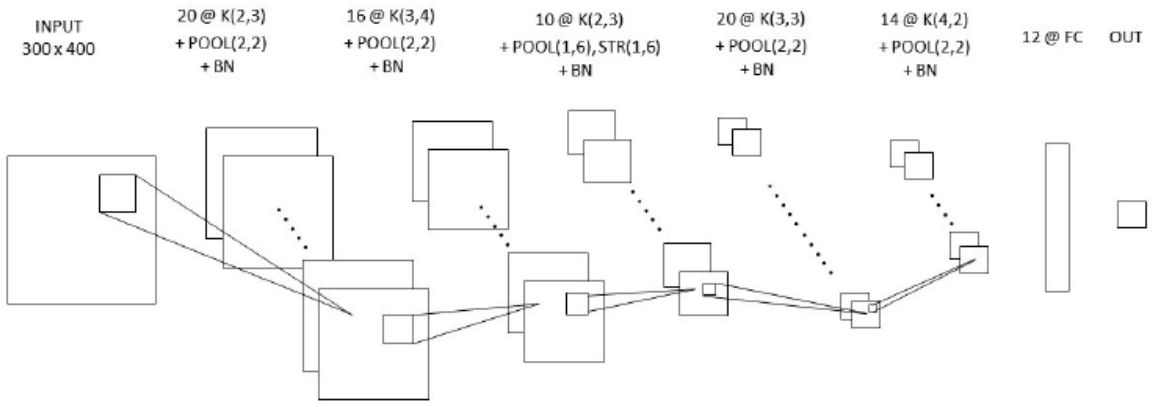


Figure27. A Convolutional Neural Network. [24]

Training was done with error back-propagation using Stochastic Gradient Descent with a decaying learning rate (0:99n), momentum = 0:5 and weight decay = 0:01, with mixed patient-dependent results.

2.5.4 Autoencoder Based System-4

Figure28 to 32 shows block diagram of all system's components. [25]

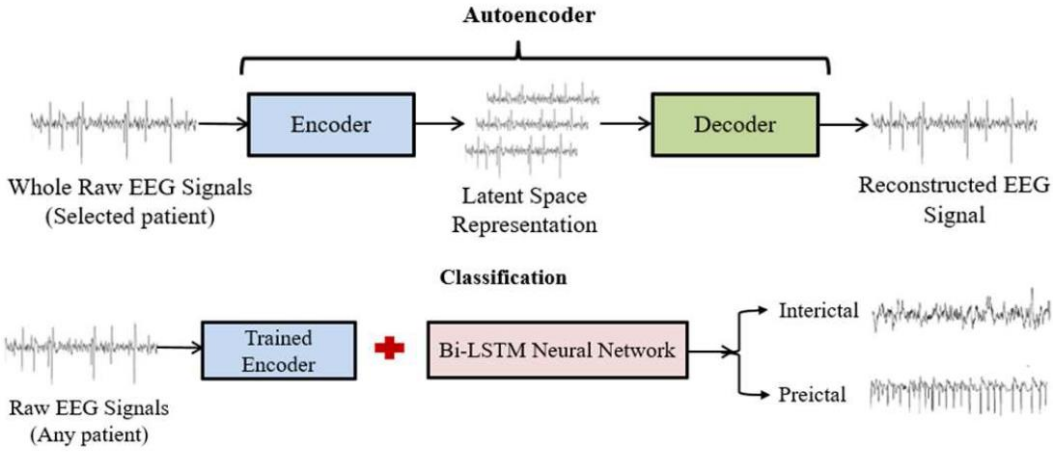


Figure 28. Block diagram of the seizure prediction system. [25]

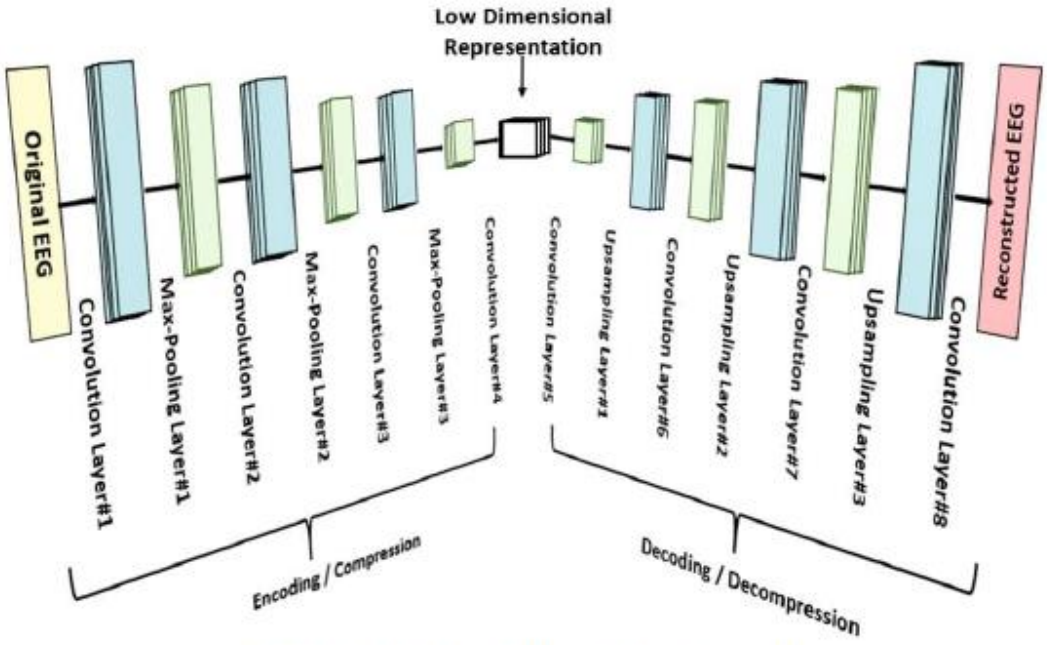


Figure 29. 2D Convolutional Autoencoder. [25]

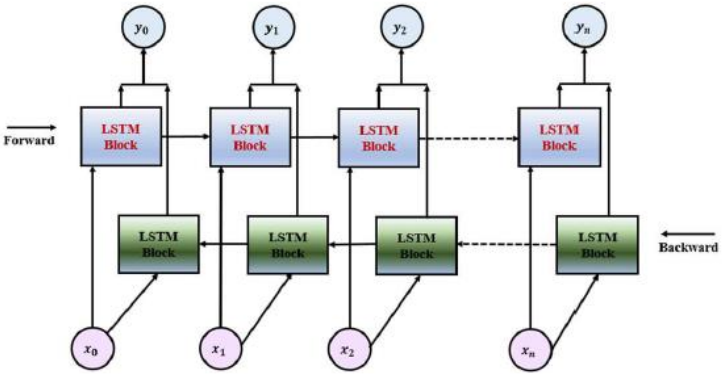


Figure 30. Bidirectional LSTM. [25]

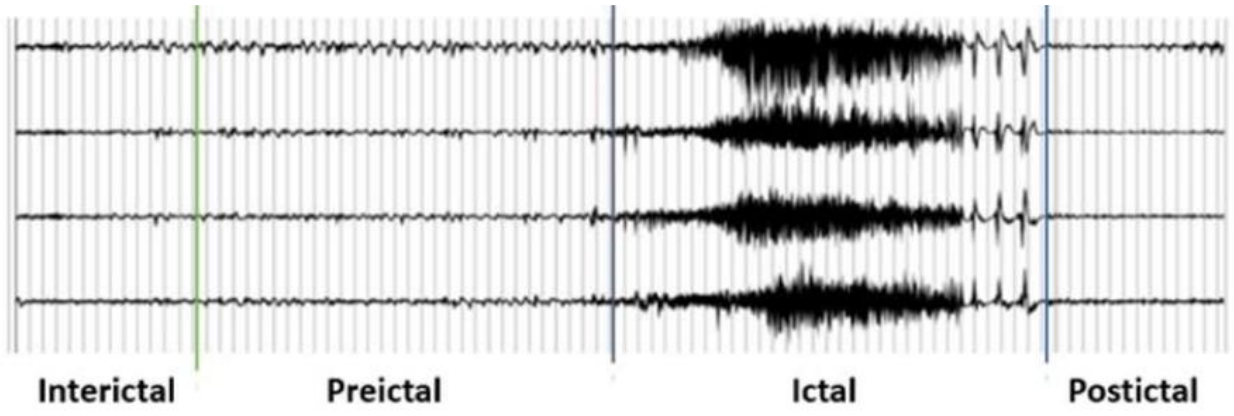


Figure 31. Seizure states. [25]

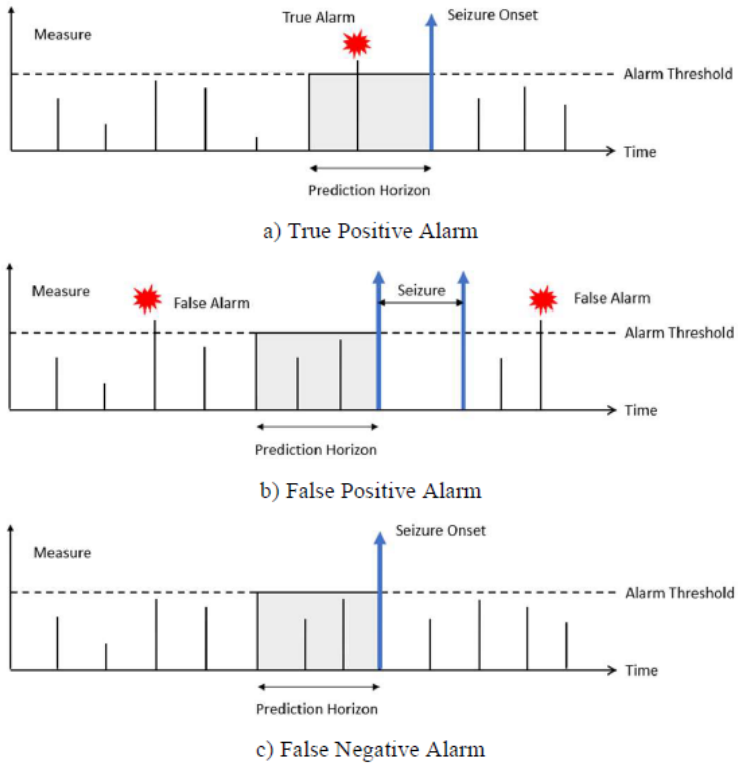


Figure 32. Seizures prediction alarms. [25]

2.5.5 CNN Based System-5

The proposed CNN and RNN are compared with the traditional machine learning algorithms, such as linear discriminant analysis and logistic regression, and the evaluation criteria are on the area under the curve. [26]

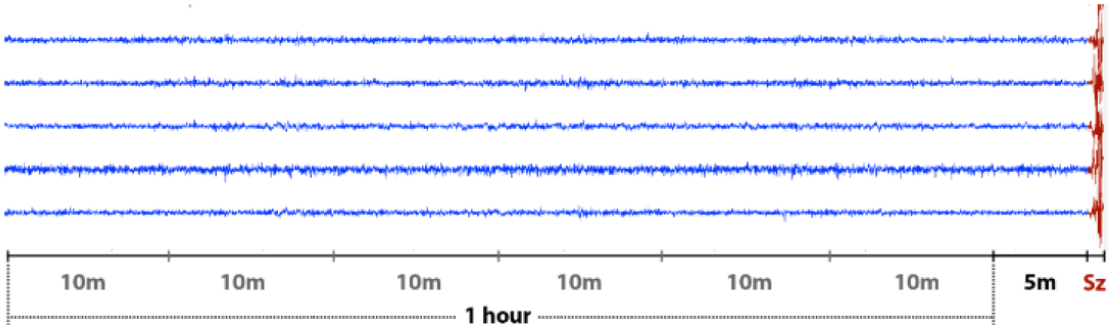


Figure 33. 1 hour and 5 minutes before seizure onset on 5 EEG channels. [26]

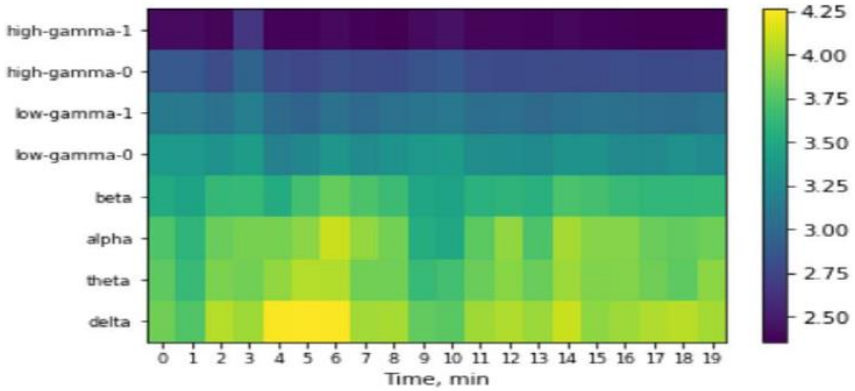


Figure 34. Spectrogram. [26]

For each 10-minute EEG data clip, specific features are extracted from the time domain voltage Figure 33.

2.6 Recent developments for Epilepsy predictor and detector systems:

2.6.1 A Deep Learning-Based Method for Automatic Detection of Epilepsy-As shown in figure- 35. [27]

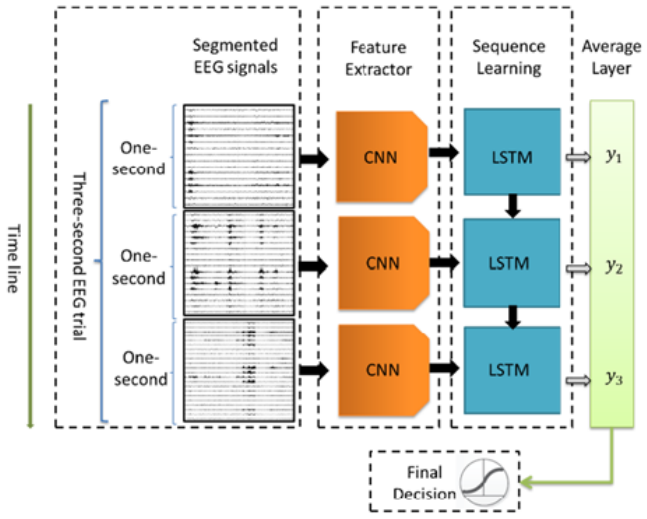


Figure 35: Framework of Deep Learning-Based Method. [27]

2.6.2 A Unified Framework of Seizure Detection and Epilepsy Diagnosis-As shown in figure- 36. [28]

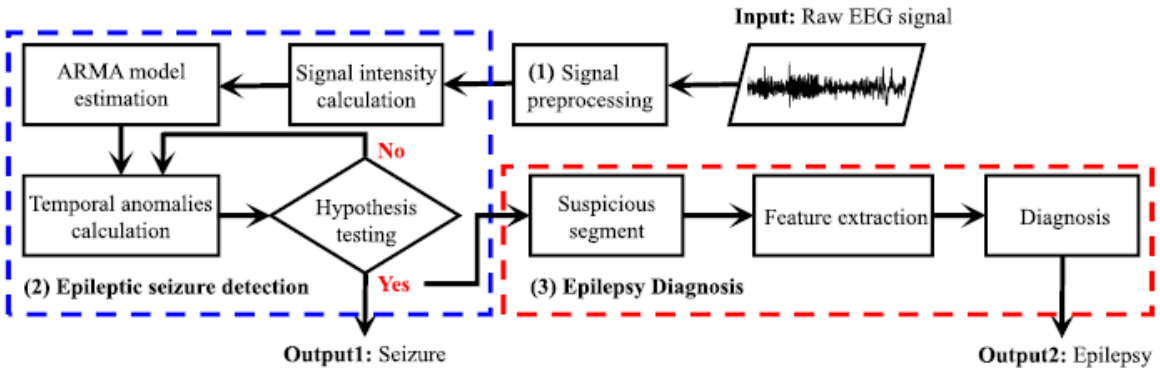


Figure 36: A unified framework. [28]

2.6.3 Entropy based detection of absence seizures-As shown in figure- 37. [29]

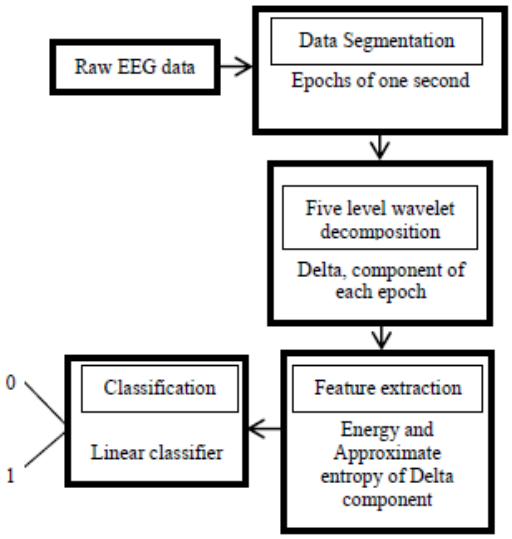


Figure 37: Framework of Entropy based automatic detection. [29]

2.6.4 ANN method for Epileptic Seizure Detection using Spatial Features- As shown in figure- 38. [30]

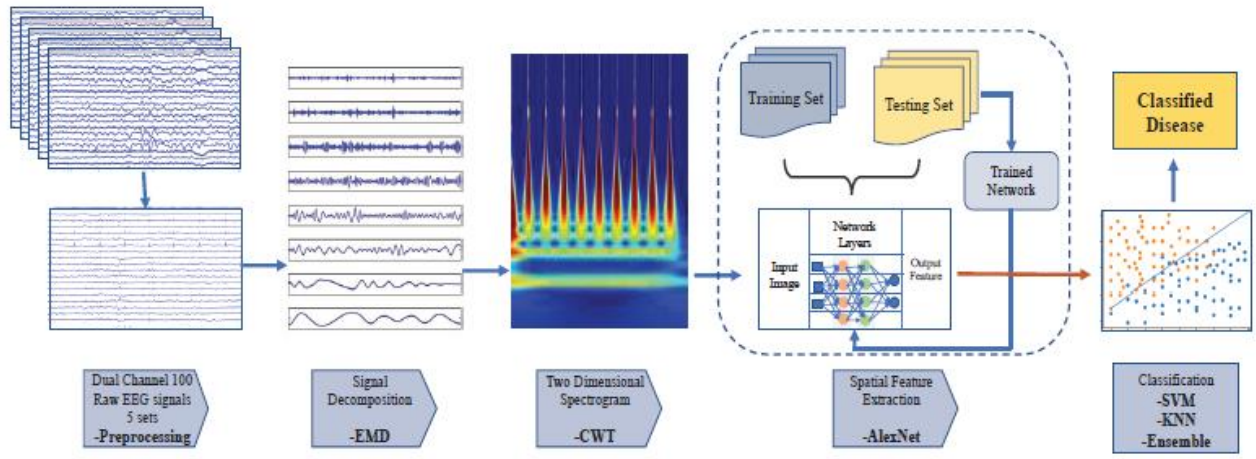


Figure 38: Framework of ANN Approach. [30]

2.6.5 An Effective Fuzzy Support Vector Machine based Seizure Detection Model- As shown in figure- 39. [31]

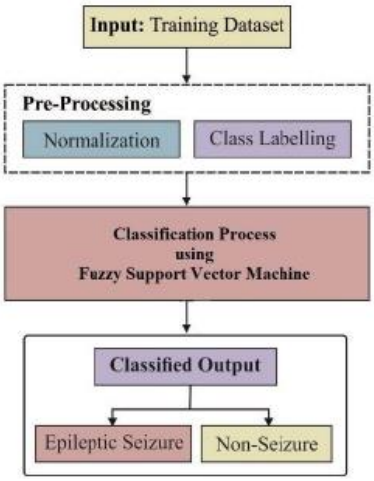


Figure 39: Framework of FSVM. [31]

2.6.6 A Deep Convolutional Neural Network Method: As shown in figure- 40. [32]

2.6.7 *A Comparative Analysis of ML Techniques* -As shown in figure- 41 and 42. [33]

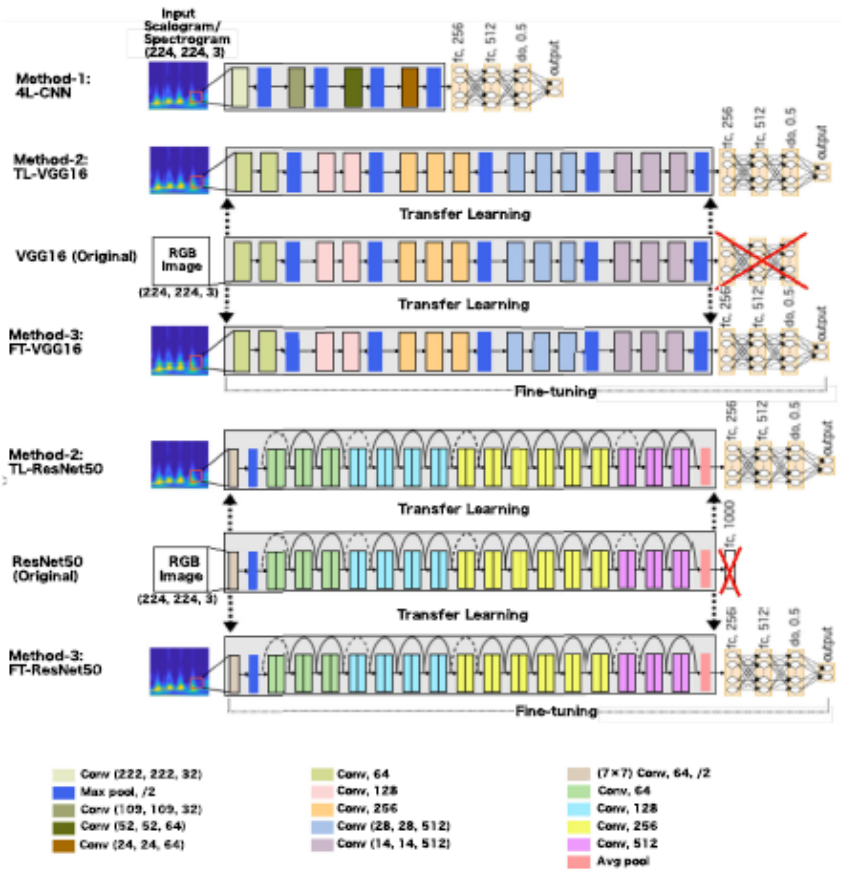


Figure 40: Framework of DCNN Method. [32]

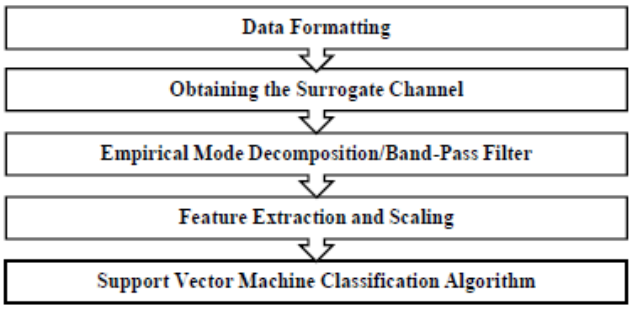


Figure 41: Framework of ML Techniques for Seizures Detection and Prediction. [33]

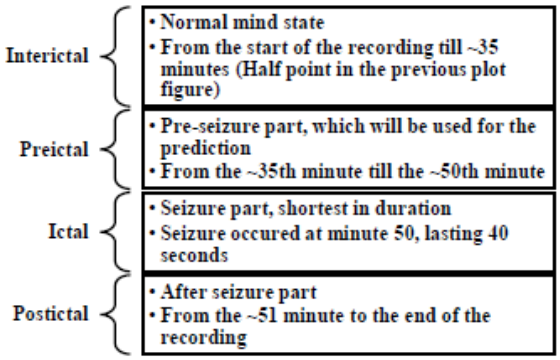

Interictal
• Normal mind state
• From the start of the recording till ~35 minutes (Half point in the previous plot figure)
Preictal
• Pre-seizure part, which will be used for the prediction
• From the ~35th minute till the ~50th minute
Ictal
• Seizure part, shortest in duration
• Seizure occured at minute 50, lasting 40 seconds
Postictal
• After seizure part
• From the ~51 minute to the end of the recording

Figure 42: Surrogate channels. [33]

2.6.8 *Epileptic Seizure Detection by Combining Dimensionality Reduction Algorithms with ML Methods*-As shown in figure- 43. [34]

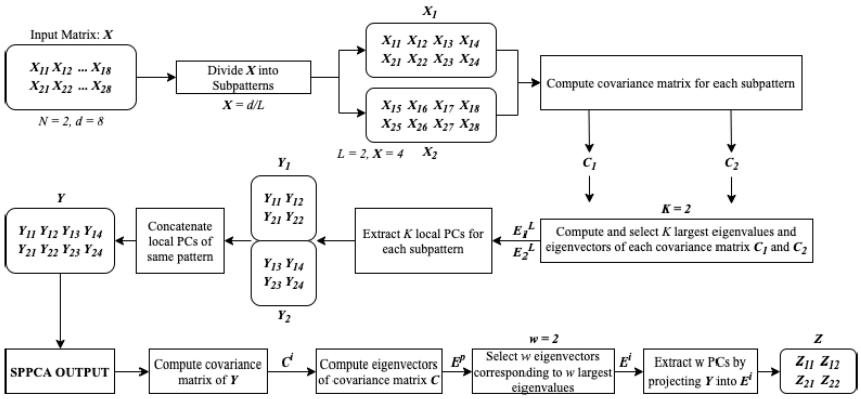

Input Matrix: X
N = 2, d = 8
Divide X into Subpatterns
X = d/L
L = 2, X = 4
X1
X2
Compute covariance matrix for each subpattern
C1
C2
K = 2
Compute and select K largest eigenvalues and eigenvectors of each covariance matrix C1 and C2
Extract K local PCs for each subpattern
Concatenate local PCs of same pattern
Y
Y1
Y2
SPPCA OUTPUT
Compute covariance matrix of Y
Compute eigenvectors of covariance matrix C
Select w eigenvectors corresponding to w largest eigenvalues
w = 2
Extract w PCs by projecting Y into E
Z

Figure 43: Framework of SPPCA and SUBXPCA. [34]

2.6.9 *Epileptic Seizure Detection Using an Integrated ML Methods*-As shown in figure- 44. [35]

2.6.10 EEG based Epileptic Seizures Detection using Intrinsic Time-Scale Decomposition- As shown in figure- 45. [36]

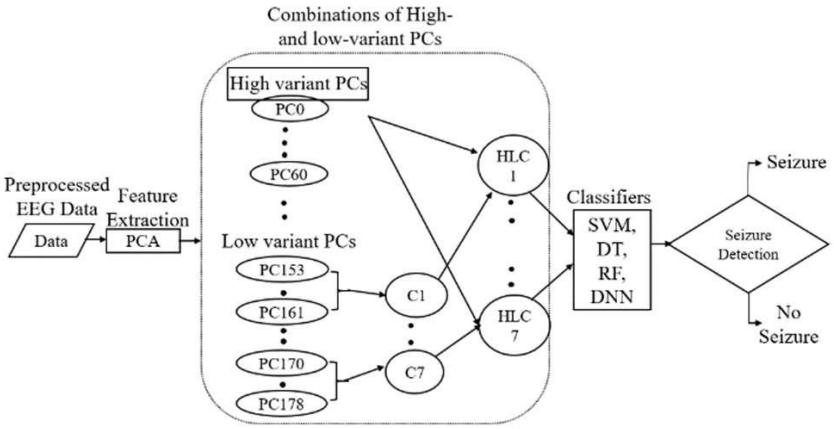


Figure 44: Framework of Integrated Machine Learning Approach. [35]

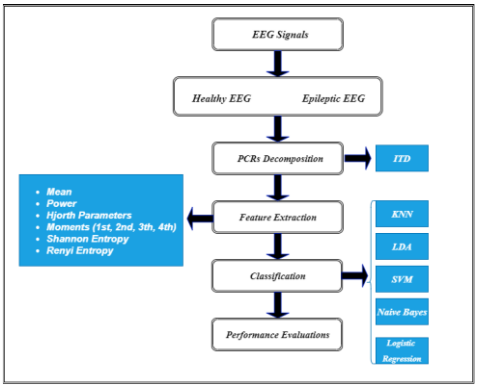


Figure 45: Framework of Epileptic Seizures Detection using Intrinsic Time-Scale Decomposition. [36]

2.6.11 A Distributed Kriging-Bootstrapped DNN Model- As as shown in figure- 46 and 47. [37]

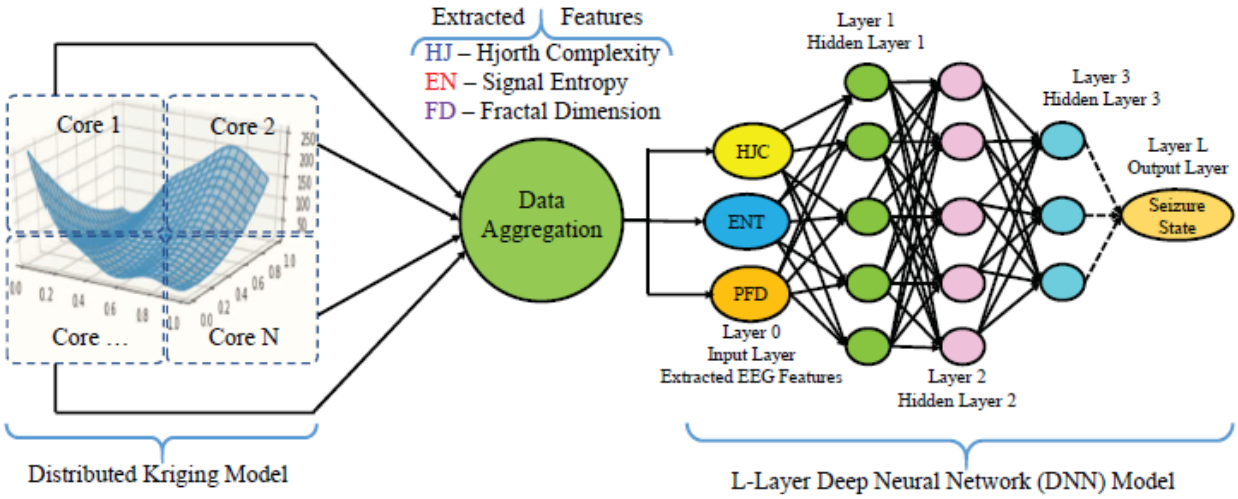


Figure 46: Framework of Distributed Kriging-Bootstrapped DNN Model. [37]

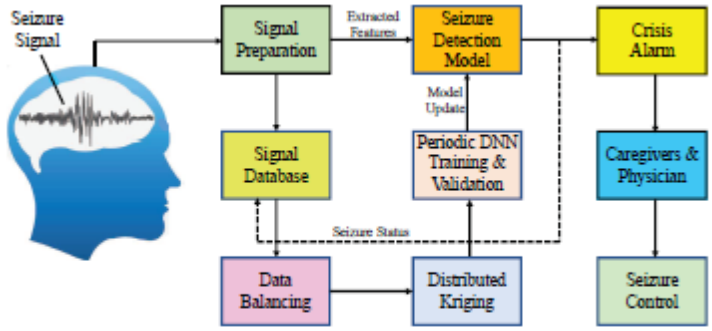


Figure 47: Framework of Fast Seizure Detection Model. [37]

2.6.12 Smart and Fully Embedded Seizure Prediction Engine: As shown in figure- 48. [38]

2.6.13 A Generalizable Seizure Detection Model- As shown in figure-49. [39]

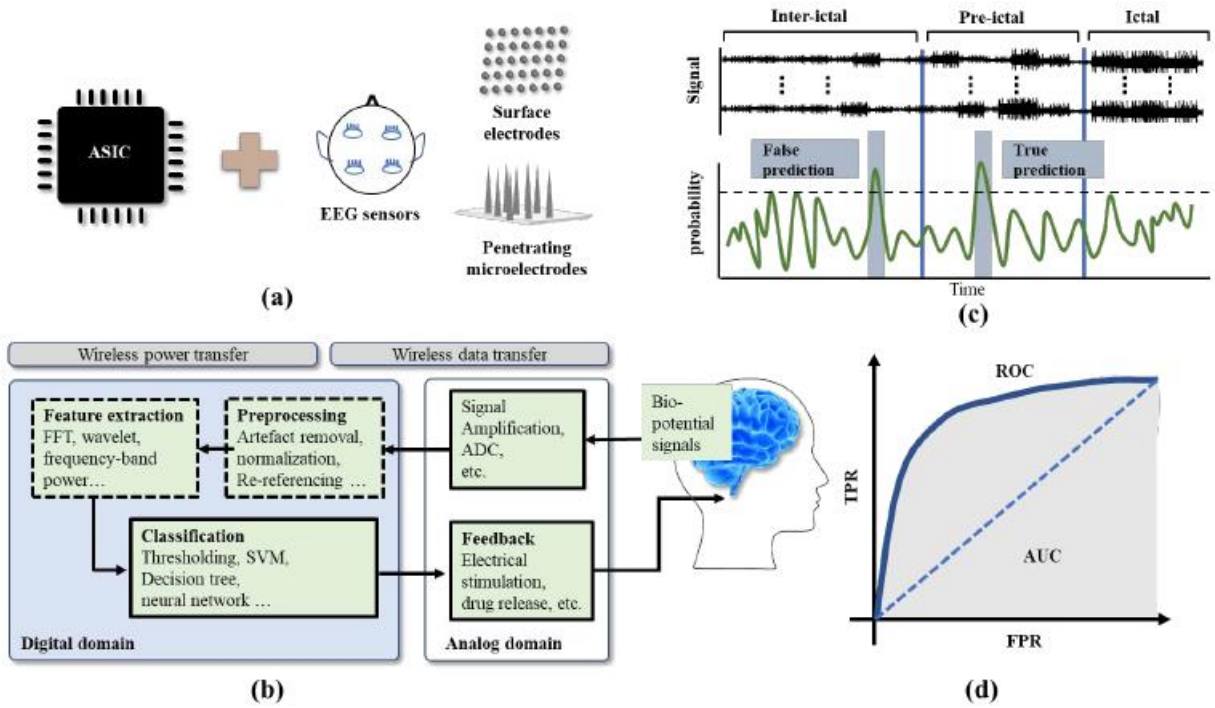


Figure 48: Framework of Smart and Fully Embedded Seizure Prediction Engine. [38]

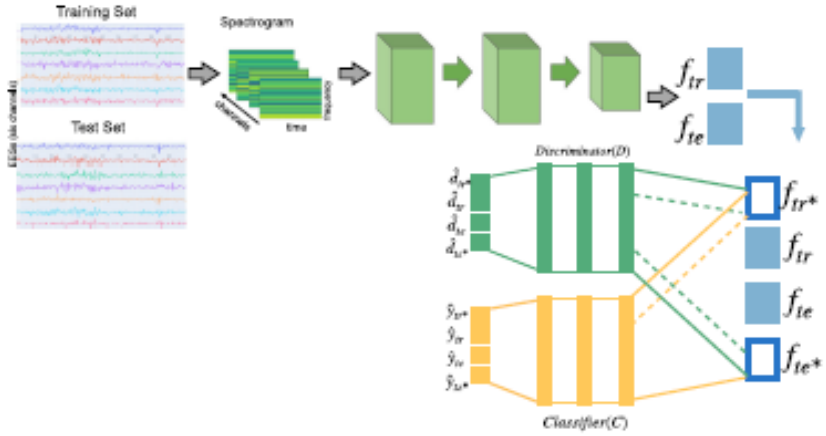


Figure 49: Framework of Generalizable Seizure Detection Model. [39]

2.6.14 A Seizure Detection Model Based on DWT-As shown in figure-50. [40]

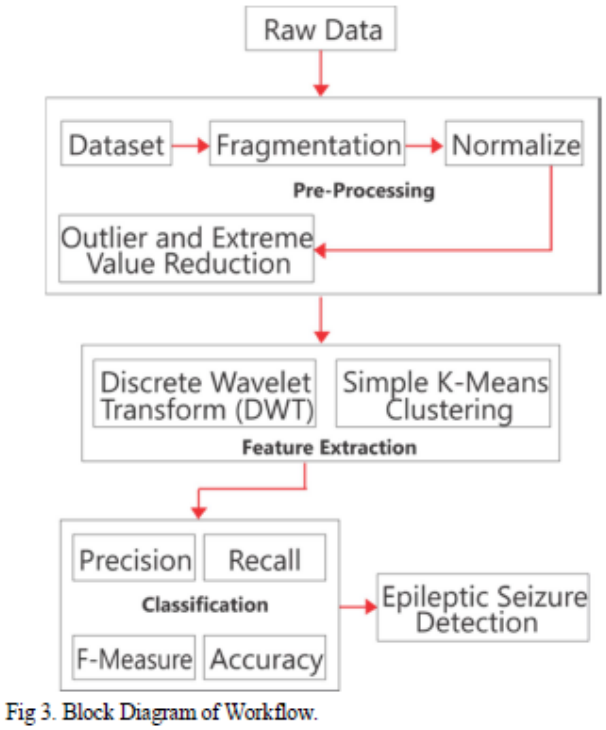


Figure 50: Framework of Classifier Based on DWT. [40]

2.6.15 An Seizure Detection Model Based on Stockwell Transform and Bi-LSTM- As shown in figure-51. [41]

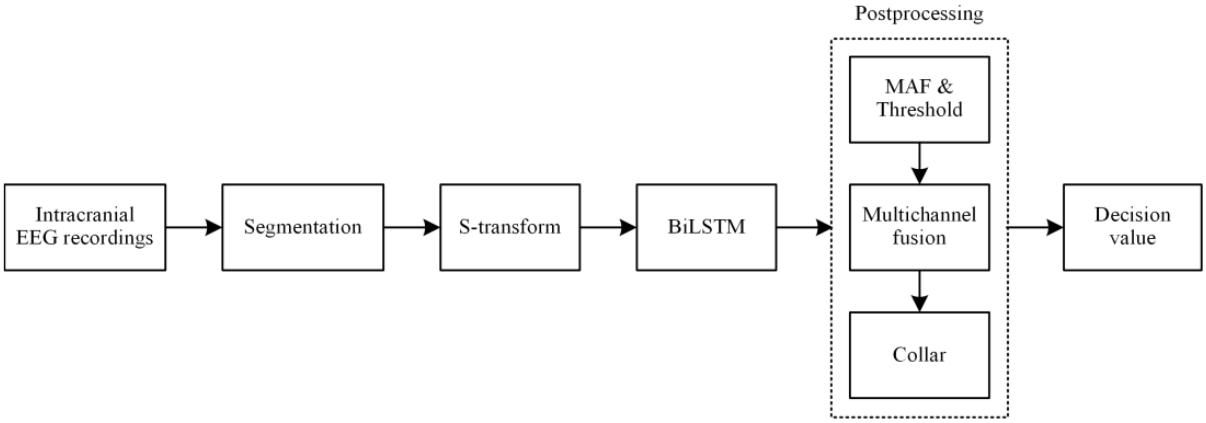


Figure 51: Framework of Seizure Detection Based on Stockwell Transform and Bi-LSTM. [41]

2.6.16 A Crow Search Based Seizure Detection Model-As shown in figure-52. [42]

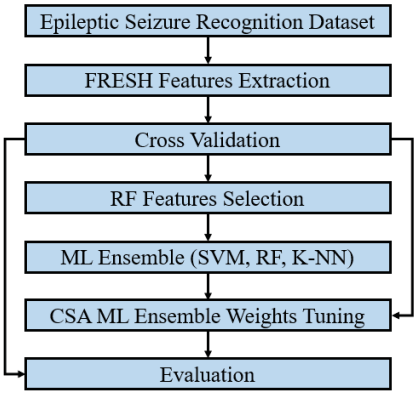


Figure 52: Framework of A *Crow Search Based Seizure Detection Model*. [42]

2.6.17 *A Robust Seizure Prediction Based on MEMD*-As shown in figure-53. [43]

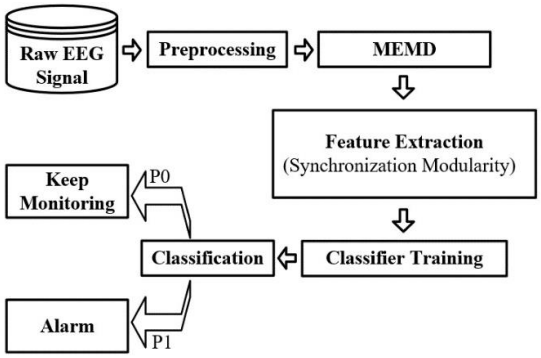


Figure 53: Framework of A Robust Seizure Prediction Model. [43]

2.6.18 Impact of Class Overlap for EEG-Based Early Epileptic Seizure Detection-As shown in figure-54. [44]

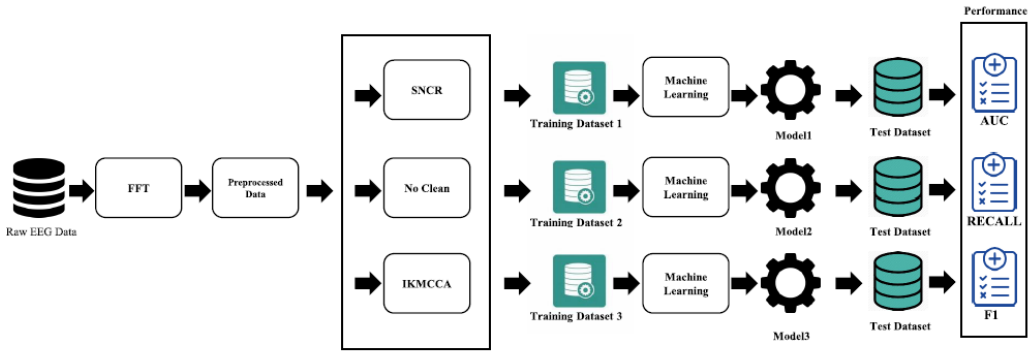


Figure 54: Framework of Early Epileptic Seizure Detection Model. [44]

2.6.19 Epileptic Seizure Detection Model by XG-boost-based Method-As shown in figure-55. [45]

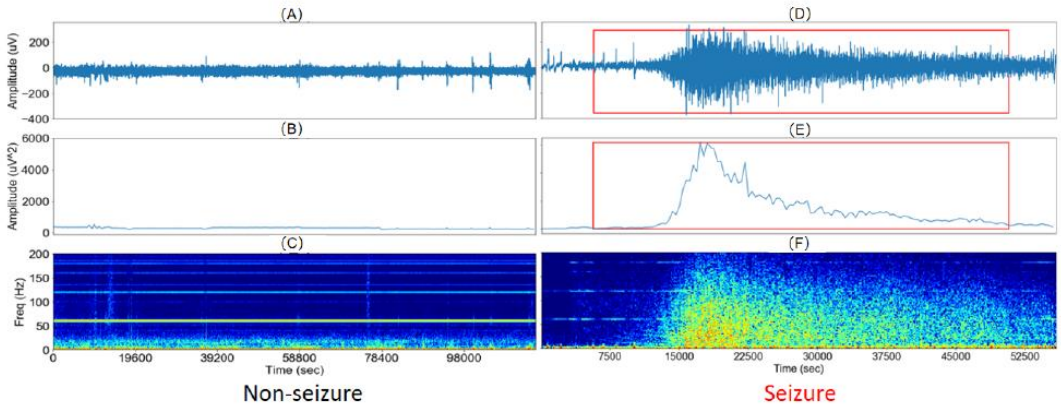


Figure 55: Epileptic Seizure Detection in Clinical EEGs Using an XGboost-based Method. [45]

2.6.20 A Spatio-Temporal Seizure Detection Model-As shown in figure-56. [46]

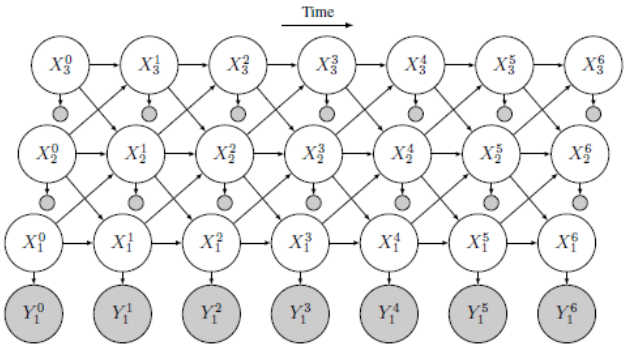


Figure 56: Framework of Spatio-Temporal Seizure Detection Model. [46]

2.7 Automatic Detection of Epilepsy

The recent developments in the EEG signal processing techniques has changed the view of long-term EEG monitoring for patients as medical people may not separate epileptic seizures from other neurological disorders like psychogenic un-epileptic attacks and convulsive scope. Detection of epilepsy visually is difficult and may take a long time. The need is to develop a wearable EEG system to alert people and doctors for upcoming seizures. It can improve the safety; reduce the death toll in epilepsy patients. [21] Implantable systems for early epileptic seizure detection are good treatment choice for patients with severe epilepsy. Most methods for early seizure prediction in the literature are not optimized for implementation on hardware embedded systems. [47]

Accurate prediction of epileptic seizures can transform medical care and medical decision systems. The improvement in seizure predictors has been affected by unavailability of alarming system in advance. Deep learning is a promising technique for seizer prediction. A combination of CNN and LSTM

networks are tested as seizure predictor using long-term EEG dataset with RNNs. [48] CNN and auto-encoders-based hardware are used for unsupervised learning. Features are extracted by hardware model and tested on two EEG data sets. The features of AE-CDNN hardware are faster learning and fast convergence system. [49]

Proposed Work

3.1 Gaps in Automatic Detection of Epilepsy.

The recent developments in the EEG signal processing techniques has changed the view of long-term EEG monitoring for patients as medical professionals lack the knowledge of separating epileptic seizures from other neurological disorders like psychogenic un-epileptic attacks and convulsive scope. Visual Detection of epilepsy by EEG signals is tedious and time consuming for long-term EEG data. The advanced signal processing technique-based methods are best for epilepsy detection automatically. The need of hour is wearable EEG devices as alarm systems for upcoming seizures for the safety of patients and reduce causalities. This requires a lot of hurdles to be overcome. One of them is limited EEG database with variability of patients. Second is to know how the ictal state ends to inform the predictor for resetting. Deep CNN optimizes as predictor. [21] Implantable, closed-loop systems for automated early epileptic seizure detection are good treatment choice for patients with severe epilepsy. Most methods for early seizure prediction in the literature are not optimized for implementation on ultra-low power microcontrollers for long-term implantation. [27]

Accurate prediction epilepsy can transform clinical epilepsy care in medical decision systems. Deep CNN and LSTM networks are used to study the large-scale unlabelled data for seizer prediction. [28] For unsupervised learning in epilepsy prediction Deep CNN and autoencoders-based model (AE-CDNN) are used by extracting features by AE-CDNN model and classify on two public EEG data sets. [49]

Materials Used: Long term RAW- EEG (sampled at 256Hz) will be used in Uni-polar Montage (64-Channels) for the research work.

(i) Features to be used for Detection are:

- RMS amplitude
- Fast Entropy

- Variance
- Skewness
- Kurtosis
- Median absolute deviation of EEG amplitude
- Coefficient of variation of the EEG signal
- Inter-quartile range
- Maximum power of the frequency bands

(ii) Features to be used for Prediction are:

- Smoothed Wigner-Ville distribution
- Spectral Power
- Spectral entropy
- Sub-bands energies
- Spectral flatness
- Renyi entropy of order α
- Phase Coherence
- STFT
- DWT

NOTE: From the list of above features most effective features will be selected with the help of Principal Component Analysis (PCA) and/or Genetic algorithm (GA).

Type of Epilepsy patients will be benefited from this research work: Following types of Epilepsy patients as shown in figure 57, will be benefitted from this research work. Out of different patients 70% can be treated with medicines but 30% patients are drug-resistant. Hence this work will help these 30% patients particularly which can be then send for surgery or VNS.

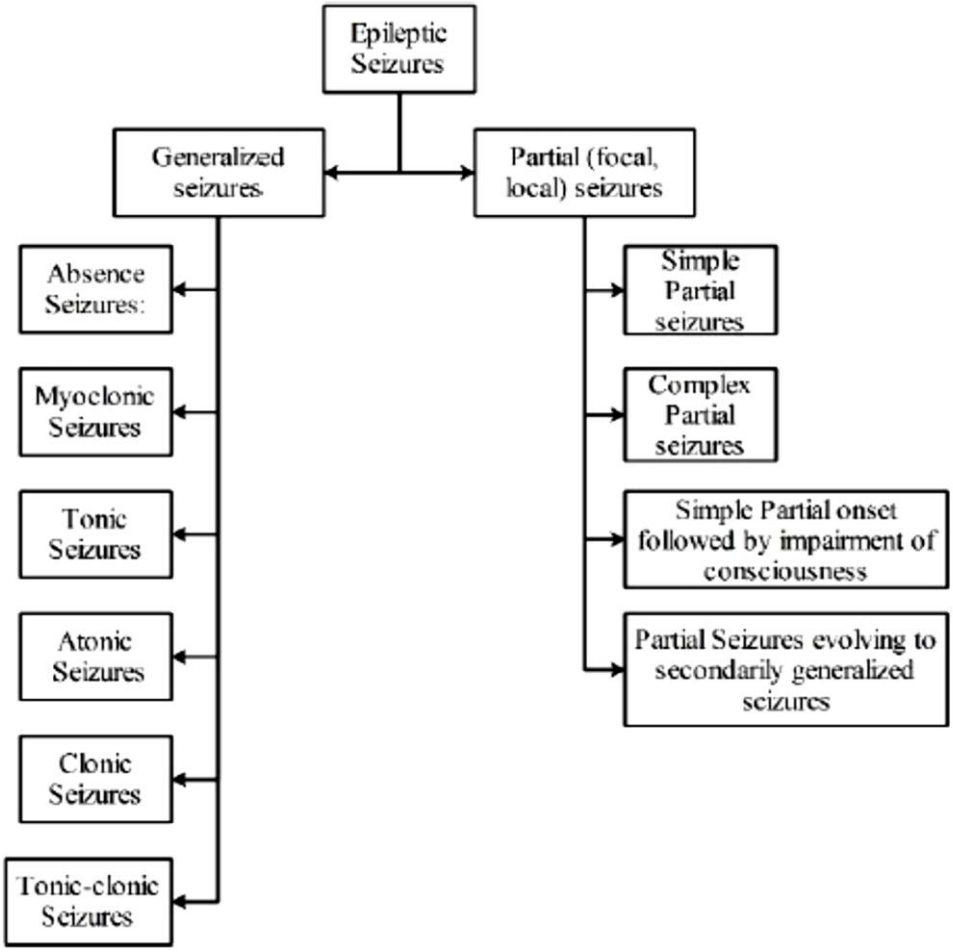


Figure 57: The Seizure Classification. [14]

3.2 Objectives of the work

The basic outline of the proposed work is as follows:

- To develop an efficient integrated soft computing approach for analysing the available EEG data.
- Automatic Detection and Prediction for multi-class classification of Epilepsy using proposed technique.
- Comparison of results of proposed technique and existing techniques.
- EEG data from two different repositories are considered for analysis and validation of the proposed system.
- Hardware Implementation for efficient and accurate Detection and Prediction of Epilepsy using proposed technique.

3.3 Problem Statement.

"To develop an automatic system for classification and prediction of seizure and non- seizure EEG signals using a soft computing integrated approach (which may include ANN, genetic algorithm, evolutionary techniques, fuzzy logic techniques, etc.) and use it for prediction of Epilepsy".

3.4 Novelty of Work.

- Generalized Epilepsy predictor and detector.
- All stages are automated as integrated in single pipeline software and hardware on FPGA/MPU.
- Prediction Time more than or equal to 60 Minutes along with accurate detection of seizures.
- Soft Computing Algorithms of predictor and detector will be tested on four different standard datasets of University of Bonn, CHB-MIT, American Epilepsy Society and UPenn and Mayo Clinic's Seizure Data.
- Scope of Cloud connectivity and IoT application.

3.5 Flow-chart of Work.

Following flow chart depicts the Methodology acquired for the present research work:

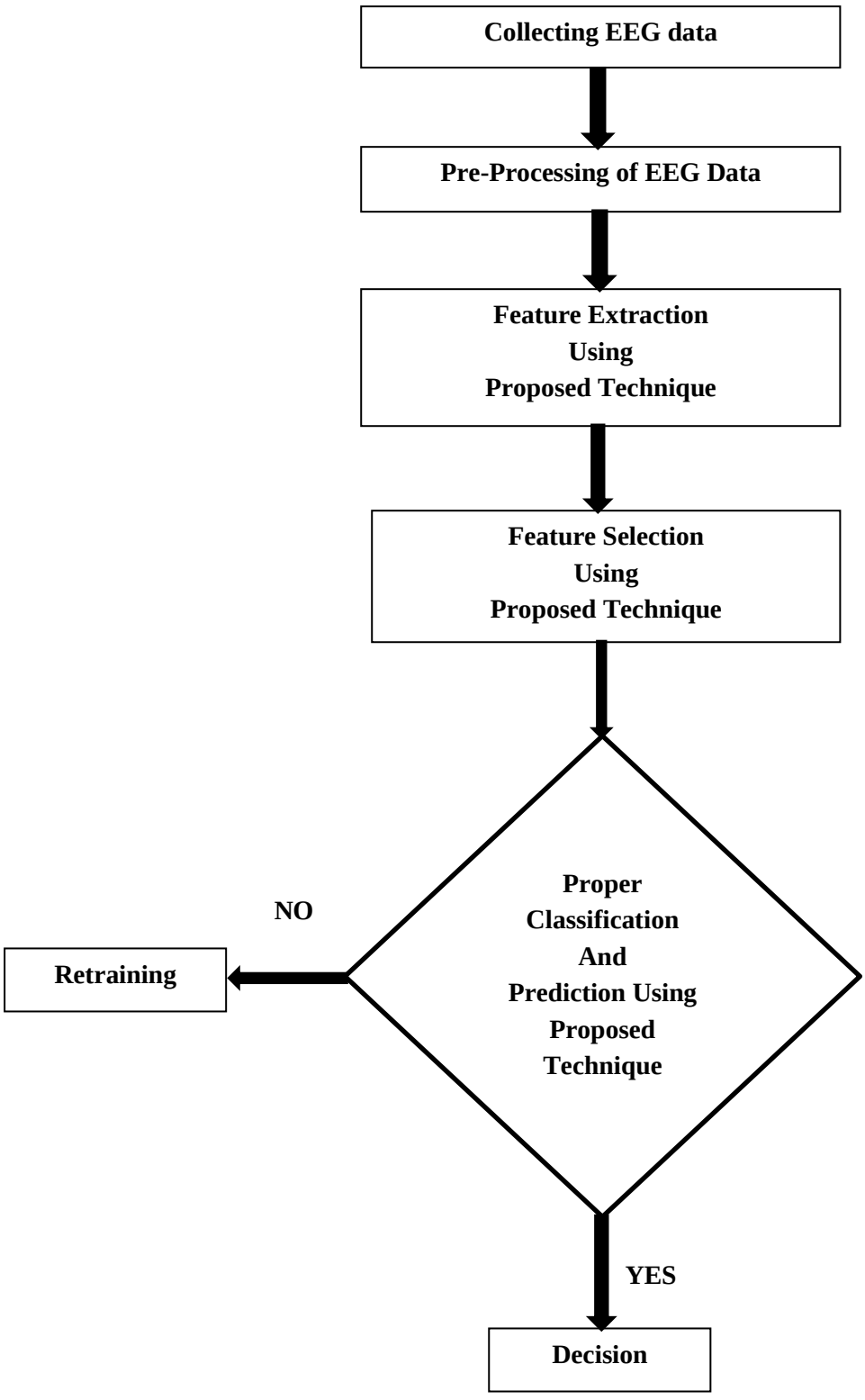


Figure 58. Methodology for the Research Work.

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